

## SHOCK WAVES: MANAGING THE IMPACTS OF CLIMATE CHANGE ON POVERTY

*Background Paper*

# The Impacts of Climate Change on Poverty in 2030 and the Potential from Rapid, Inclusive, and Climate-Informed Development

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## Abstract

The impacts of climate change on poverty depend on the magnitude of climate change, but also on demographic and socioeconomic trends. An analysis of hundreds of baseline scenarios for future economic development in the absence of climate change in 92 countries shows that the drivers of poverty eradication differ across countries. Two representative scenarios are selected from these hundreds. One scenario is optimistic regarding poverty and is labeled “prosperity;” the other scenario is pessimistic and labeled “poverty.” Results from sector analyses of climate change impacts—in agriculture, health, and natural

disasters—are introduced in the two scenarios. By 2030, climate change is found to have a significant impact on poverty, especially through higher food prices and reduction of agricultural production in Africa and South Asia, and through health in all regions. But the magnitude of these impacts depends on development choices. In the prosperity scenario with rapid, inclusive, and climate-informed development, climate change increases poverty by between 3 million and 16 million in 2030. The increase in poverty reaches between 35 million and 122 million if development is delayed and less inclusive (the poverty scenario).

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# The Impacts of Climate Change on Poverty in 2030 and the Potential from Rapid, Inclusive, and Climate-Informed Development

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## 1. Introduction

Estimates of the economic cost of climate change have attracted interest from policy makers and the public and generated heated debates. These estimates, however, have mostly been framed in terms of the impact on country-level or global GDP, which does not capture the full impact of climate change on people's well-being.

In particular, climate change impacts will be highly heterogeneous within countries. If impacts mostly affect low-income people, welfare consequences will be much larger than if the burden is borne by those with a higher income. Poor people have fewer resources to fall back upon and lower adaptive capacity. And – because their assets and income represent such a small share of national wealth – poor people's losses, even if dramatic, are largely invisible in aggregate economic statistics.

Investigating the impact of climate change on poverty requires an approach that focuses on people that play a minor role in aggregate economic figures and are often living within the margins of basic subsistence. Macroeconomic models such as Computable General Equilibrium models alone cannot assess the impact on poverty, and a micro-economic approach that explicitly represents the livelihoods of poor people is required. Fortunately, micro-simulation techniques (Olivieri et al. 2014; Bussolo, De Hoyos, et al. 2008; Bourguignon, Ferreira, and Lustig 2005) and the generalization of household surveys now make it possible to look at this issue. Innovative steps in this direction have been made recently, combining aggregate impact estimates with household-level data or using specific models (Hertel and Rosch 2010; Hertel, Burke, and Lobell 2010; Ahmed, Diffenbaugh, and Hertel 2009; Gupta 2014; Jacoby, Rabassa, and Skoufias 2014; Skoufias, Rabassa, and Olivieri 2011; Devarajan et al. 2013; Bussolo, de Hoyos, et al. 2008). Most of these analyses investigate the effect of climate change on poverty through agriculture production.

Assessing the impact of climate change on poverty remains however a daunting task. In particular, the speed and direction of future socioeconomic changes will determine the future impacts of climate change on poor people and on poverty rates as much as climate change itself (Hallegatte, Przulski, and Vogt-Schilb 2011). It is not hard to imagine that, in a world where everyone has access to water and sanitation, the impacts of climate change on water-borne diseases will be smaller than in a world where uncontrolled urbanization has led to widespread underserved settlements located in flood zones. Similarly, in a country whose workers mostly work outside or without air conditioning, the impact of temperature increase on labor productivity will be stronger than in an industrialized economy. And a poorer household will have a larger share of its consumption dedicated to food and will therefore be more vulnerable to climate-related food price fluctuations than a richer household.

Assessing the future impacts of climate change therefore requires an exploration of future socioeconomic development pathways, in addition to future changes in climate and environmental conditions.

First, we assume that there is no climate change, and we explore possible counterfactual scenarios of future development and poverty eradication. Second, we introduce climate change into the picture and look at how it changes the prospect for poverty eradication.

It is impossible to forecast future socioeconomic development. Past experience suggests we are simply not able to anticipate structural shifts, economic crises, technical breakthroughs, and geopolitical changes (Kalra, Gill, et al. 2014). In this paper, we neither *predict* future socioeconomic change nor the impact of climate change on poverty. Instead, we follow the approach that is the basis of all IPCC reports, namely we analyze a set of *socioeconomic scenarios* and we explore how climate change would affect development in *each* of these scenarios. These scenarios do not correspond to particularly likely futures. Instead, they are possible and internally consistent futures, chosen to cover a broad range of possible futures to allow for an exploration of possible climate change impacts. People sometimes refer to these scenarios as “what-if” scenarios, as they can help answer questions such as “*what* would climate change impact be *if* socioeconomic development followed a given trend.” The goals are to better understand how the impact of climate change on poverty depends on socioeconomic development, to estimate the potential impacts in “bad” scenarios, and to explore possible policy options to minimize the risk that such bad scenarios actually occur.

We start by analyzing the drivers of future poverty, and we explore the range of possible futures regarding these drivers to create hundreds of socioeconomic scenarios for each of the 92 countries we have in our database. This analysis combines household surveys (from the I2D2 database) and micro-simulation techniques (Olivieri et al. 2014; Bussolo, De Hoyos, et al. 2008; Bourguignon, Ferreira, and Lustig 2005) and is performed in a framework inspired from robust decision-making techniques, in which all uncertain parameters are varied systematically to the full range of possible outcomes. We combine assumptions on future demographic changes (How will fertility change over time? How will education levels change?); structural changes (How fast will developing countries grow their manufacturing sector? How will the economies shift to more services?); productivity and economic growth (How fast will productivity grow in each economic sector?); and policies (What will be the level of pensions? How much redistribution will occur?). The range of possible futures of these parameters is determined based on historical evidence, and on the socioeconomic scenarios currently developed for the analysis of climate change, the Shared Socio-Economic Pathways (SSPs) (Kriegler et al., n.d.; O’Neill et al. 2013). These sets of assumptions are used to generate hundreds of scenarios for the future socioeconomic development of each of 92 countries.

Then, we select two representative scenarios per country, one optimistic and one pessimistic in terms of poverty reduction and changes in inequality, and we aggregate them into two global scenarios. A first scenario is labelled “prosperity” and represents a world with universal access to basic services, a reduction in inequality, and the reduction of extreme poverty to less than 3% of the world population (this is one of the two official goals of the World Bank Group).<sup>2</sup> A second scenario is labelled “poverty” and represents a world where poverty is reduced, but not to an extent consistent with the goals of the international community, where access to basic services improves only marginally and inequality is high.

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<sup>2</sup> In this paper, extreme poverty is defined using a consumption poverty line at US\$1.25 per day, using 2005 PPP exchange rates. Using the new poverty line (with 2011 PPP rates and the \$1.90 line, see GMR, 2015) would not change our results in a quantitative manner, considering the consistency between the two PPP rates (Jolliffe and Prydz 2015) and the way we treat the uncertainty on poverty numbers.

Finally, we introduce quantified estimates of the impacts of climate change on agriculture incomes and food prices, on natural hazards, and on malaria, diarrhea and stunting into these two scenarios. With a 2030 horizon, impacts barely depend on emissions between 2015 and 2030 because these affect the magnitude of climate change only over the longer term, beyond 2050. Regardless of socioeconomic trends and climate policies, the mean temperature increase between 2015 and 2035 is between 0.5 and 1.2°C— and the magnitude depends on the response of the climate system (IPCC 2013). The impacts of such a change in climate are highly uncertain and depend on how global climate change translates into local changes, on the ability of ecosystems to adapt, on the responsiveness of physical systems such as glaciers and coastal zones, and on spontaneous adaptation in various sectors (such as adoption of new agricultural practices or improved hygiene habits). We thus consider again two cases, one high impact and one low impact, and investigate the potential impact of unmitigated climate change on the number of poor people living in extreme poverty in 2030 in the four cases (optimistic and pessimistic regarding socioeconomic trends, and optimistic and pessimistic regarding climate change impacts).

We reach several conclusions that are relevant for the future of poverty and poverty reduction policies.

First, we find that – in our hundreds of scenarios per country – indicators for poverty and inequality are not correlated, and are not driven by the same parameters. This suggests that policy priorities linked to poverty or shared prosperity may be very different. For instance, the variables that matter the most for increasing the income of the bottom 20% (an indicator for poverty) in many countries are demographic changes, welfare transfers and productivity growth for unskilled workers in the agriculture and service sectors. For inequality, the most important uncertain parameters are welfare transfers and the skill premium in the service sector (which has to remain relatively low to prevent inequality growth). Note however that this is not the case for all countries. In central Europe, for instance, increase in participation in the labor force is a determining factor for increasing the income of the bottom 20%.

Second, we find that the drivers of success in reducing poverty differ across countries. We find for instance that population and education are the main drivers for most African countries, while labor force participation is more important in central Europe. Redistribution is also found to be an instrument for reducing poverty, except in very poor countries that do not have the resources to make a dent in poverty by redistributing income. We also identify countries where poverty reduction efforts should focus on unskilled agriculture, while this parameter plays a secondary role in others. This result confirms the fact that poverty reduction strategies have to be context-specific and depend on one country's socioeconomic situation. It also suggests that some countries have higher vulnerability to climate change, for instance where agriculture income will play a dominant role in reducing poverty.

We also present findings regarding the impact of climate change on poverty, keeping in mind that climate change is moderate in 2030 compared with what can be expected over the longer-term. Nevertheless, climate change still has a visible impact on our poverty projections at this horizon, even if it remains a secondary driver of poverty trends (compared with policies and socio-economic trends). We also find that, by 2030 and in the absence of surprises on climate impacts, inclusive climate-informed development can prevent most of (but not all) the impacts on poverty.

In a scenario with inclusive climate-informed development that would provide universal access to basic services such as water and sanitation and achieve the World Bank goal of bringing extreme poverty to 3% in 2030 in the absence of climate change (the *Prosperity* scenario), climate change reduces income in developing countries by between 0.5% and 2.2%, and increases the number of poor people by between 3 million and 16 million in 2030.

In a scenario where poverty persists, with 11% of the population in extreme poverty in 2030, and unchanged access to basic services (the *Poverty* scenario), climate change impacts on aggregate income are similar (a reduction between 0.7% and 2.6% of aggregate income in developing countries), but poverty impacts are much larger with between 35 million and 122 million more people in extreme poverty. Development appears to reduce the impact of climate change on poverty much more than it reduces aggregated losses expressed in percentage of GDP.

In these two scenarios, the most important channel through which climate change increases poverty is through agricultural income and food prices, because agricultural impacts are the most severe in Sub-Saharan Africa and India, where most poor people live in 2030. In both the poverty and prosperity scenario, therefore, the regional hotspots are Sub-Saharan Africa and India and the rest of South Asia.

## 2. Methodology

The first stage of our methodology is to build, for each country, many scenarios for possible future socioeconomic change. To do so, we explore a wide range of uncertainties on future structural change, productivity growth, demographic changes, and policies, to create several hundred scenarios for future income growth and income distribution in each country. We then explore the resulting space of possible future poverty and income distribution using indicators like income of the bottom 20%, number of people below \$4 or \$6 per day, income share of the bottom 40%, the Gini index, etc.

The second stage is to use scenario discovery techniques (Groves and Lempert 2007) to identify the conditions under which some poverty outcome is most likely. For instance, we can identify the demographic, economic, and policy conditions in which the average income of the bottom 20% is most likely to be higher than \$2 per day in 2030 in Sierra Leone. These scenario discovery techniques tell us about the key determinants of various outcomes – such as eradicating extreme poverty – and therefore about the policies that can help achieve this goal.

### 2.1. Micro-simulation model

We use a micro-simulation model based on household surveys and, for each country, project the pathway of individuals in the economy (the Appendix gives all details of the model). Micro-simulation models represent dozens of thousands of individuals per country, which are all assigned a weight so that the entire population is modeled. Each individual is characterized by age, sex, level of education, employment, income etc.

First, we assign a category to each individual in the model, based on his/her age, skill level and sector of activity (or his/her inactivity):<sup>3</sup> (1) unskilled services worker; (2) skilled service worker; (3) unskilled agriculture worker; (4) skilled agriculture worker; (5) unskilled manufacture worker; (6) skilled manufacture worker; (7) adult not in the labor force; (8) elderly (above 65 years-old); (9) child (under 15 years-old).<sup>4</sup> These categories consider 3 sectors (services, industry and agriculture) divided into lower-return and higher-return activities as reflected by skills.

Second, we “project” households into the future, in 2030. We change the income and weight of each household in the model to reflect macro-economic changes. The households weights are adjusted so that the total population matches different age and skills compositions of the population, participation in the labor force, and the labor share of each sector, based on demographics scenarios developed for the SSPs (Samir and Lutz 2014) and assumptions on structural change. This reweighting process models demographic changes (e.g. older people or more skilled people) and structural transformations (e.g. less people in unskilled agriculture). Incomes of each individual then evolve over time, based on the productivity growth and skill premiums for the sector the individual belongs to, and on income redistribution. The existing variance in income in each household category is assumed unchanged (if we have 500 individuals that are skilled farmers, for instance, they have different income levels and this variance is assumed unchanged by 2030, which means that all individuals in one category see their income multiplied by the same amount). The inequality and poverty we have in our scenario is a combination of within category variance (assumed unchanged) and across-category variance (which changes with structural and productivity changes).

This approach can provide estimates of income distribution and poverty at different point of time, but it does not represent the full dynamics of poverty or the distinction between chronic and temporary poverty – an important limitation considering the large and frequent movements in and out of poverty observed in developing countries (Lanjouw, McKenzie, and Luoto 2011; Krishna 2006; Baulch 2011; Dang, Lanjouw, and Swinkels 2014; Beegle, De Weerd, and Dercon 2006).

Overall, the changes in income and weight of each household are driven by 12 uncertain parameters reflecting:

- demographic changes, including population growth, age and skills (represented by 1 unique parameter, to keep the consistency in demographic assumption);
- structural transformations, reflected by the change in the share of labor force in each sector (2 parameters) and participation in the labor force (1 parameter);

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<sup>3</sup> Since the database reports only one sector of activity per individual, we are not able to account for the fact that many poor people may have multiple jobs and income sources.

<sup>4</sup> As per WB definition, a worker is defined as skilled if he has more than nine years of education.



- income changes based on productivity growth in each sector (3 parameters), skill premiums in each sector (3 parameters), pensions and social transfers (2 parameters).

Due to the uncertainty inherent in projecting these drivers, we work with a range of values for each of these parameters. These ranges are based on historical data and trends and on previous work on socioeconomic scenarios such as the development of the SSPs.

**Demography.** For demographic changes, these ranges were chosen based on population data (total population by age, sex, education) developed by IASA for the SSP4 and SSP5 (Samir and Lutz 2014).

**Structural change.** The plausible ranges are based on the initial economic structure of each country and projected pathways, using the minimum and maximum change observed in historical data over the last 20 years to estimate the boundaries of possible future structural change.

**Participation** (i.e. the share of 15-64 years who have a job). To define a plausible range of uncertainty for this variable, we look at available historical data for all countries and all periods of time and choose boundaries slightly larger than the lowest and highest rates of change over 20 years in employment (see Appendix).

**Productivity growth.** We use a different productivity growth rate for each the three main sectors of the economy (agriculture, industry and services). This growth rate is applied to the income of unskilled workers. The income of skilled workers will then increase with regards to the income of unskilled workers with a skill premium (here again, different a priori for each sector). For unskilled workers productivity growth rate, we calculate a range based on GDP growth in the SSPs (Chateau et al. 2012) and on the working age population growth, to make sure the range of total income growth resulting from our micro-simulation is centered around (but larger than) the SSP range. For the skill premium we use a range of 1 to 5 (this is the current range across countries). The total productivity growth is an output of the model, as it depends on productivity growth for unskilled workers, on the skill premium and on the share of skilled workers in each sector (Rodrik 2011).

**Pensions and social transfers.** We model two types of redistribution. The first one is a universal cash transfer (or basic income, distributed to each individual aged more than 15), financed by a flat consumption tax. The second transfer represents the pensions: we model a flat tax on workers' income and use it for cash transfers to individuals older than 65 years. The amount of the cash transfers distributed to each individual therefore depends on the level of the two taxes and on total consumption (or income) in the economy. We use a range of 0-20% for each tax.

To generate the scenarios, we use a latin hypercube sampling algorithm<sup>5</sup> that selects a few hundred combinations of parameters within the chosen ranges. Based on each combination of different parameter values, we produce several hundred projections of one individual into the future. This process results in a database of 1,200 scenarios of future poverty and distribution outcomes per country.

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<sup>5</sup> The latin hypercube sampling algorithm maps the n-dimension space of uncertainty so that a minimum number of scenarios cover as densely as possible the full space.

Since we combine many different possible values for all drivers, which we treat as independent, we disregard macro-economic coherence *a priori*. For instance, nothing prevents us from running a scenario with very high productivity growth in agriculture and no growth in the other sectors of the economy, or a scenario with a skill premium of 1 in services and 5 in industry. Other methodologies combine a macroeconomic model with micro-simulation to ensure consistency across sectors (Boccanfuso, Decaluwé, and Savard 2008; Ahmed et al. 2014; Bussolo, De Hoyos, et al. 2008). In this analysis, the lack of international consistency is not an issue as we are not trying to predict the future but we are rather looking for the *necessary* conditions (on those drivers) to reduce poverty. The plausibility and coherence of these conditions will be investigated *ex-post* when selecting the representative scenarios. Also, there is a well-established trade-off between the internal consistency of scenarios and the risk of being too conservative – for instance by assuming that the relationship between two variables will remain unchanged over time. Here, we favor the exploration of a large set of possible futures, and consider consistency only in the second phase, when representative scenarios are selected.

Finally, we do not attribute probabilities or likelihood to our scenarios. These scenarios thus cannot be used as forecasts or predictions of the future of poverty or as inputs in a probabilistic cost-benefit analysis. That said, they can still be an important input into decision-making. Indeed, decisions often are not based on average or expected values or on the most likely outputs, but instead on the consequences of relatively low-probability outcomes. For instance, insurers and reinsurers are often regulated based on the 200-year losses (that is, the losses that have a 0.5 percent chance of occurring every year).

Moreover, in a situation of deep uncertainty, it is often impossible to attribute probabilities to possible outcomes (Kalra, Hallegatte, et al. 2014). For example, we know that conflicts, such as those in North Africa and the Middle-East, could continue over decades, preventing growth and poverty reduction. But they also could subside, allowing for rapid progress. While these two scenarios are obviously possible, it is impossible to attribute probabilities to them in any reliable way. The same deep uncertainty surrounds the future of technologies and most political and socioeconomic trends. In such a context, exploring scenarios without attributing probabilities to them is commonplace. The IPCC and climate community have used such long-term socioeconomic scenarios (the SRES and now the SSPs) since the 1990s, to link policy decisions to their possible outcomes (Edenhofer and Minx 2014). Similarly, the UK government performs national risk assessments using “reasonable worst case scenarios” (for example, regarding pandemics, natural disasters, technological accidents or terrorism), which are considered plausible enough to deserve attention, even though their probability is unknown (World Bank 2013, chapter 2).

While these scenarios cannot be used to perform a full cost-benefit analysis, they make it possible to elicit trade-offs and to support decision-making. For instance, they help identify dangerous vulnerabilities that can be removed through short-term interventions (Kalra, Hallegatte, et al. 2014). In our case here, our scenarios help us explore and quantify how poverty reduction can reduce the vulnerability to climate change.

## 2.2. Indicators for poverty and inequality

In our scenarios, the number of people living below the extreme poverty line, the average income of the bottom 20%, and the income growth of the bottom 40% are very well correlated (more than 90% correlation for all countries).

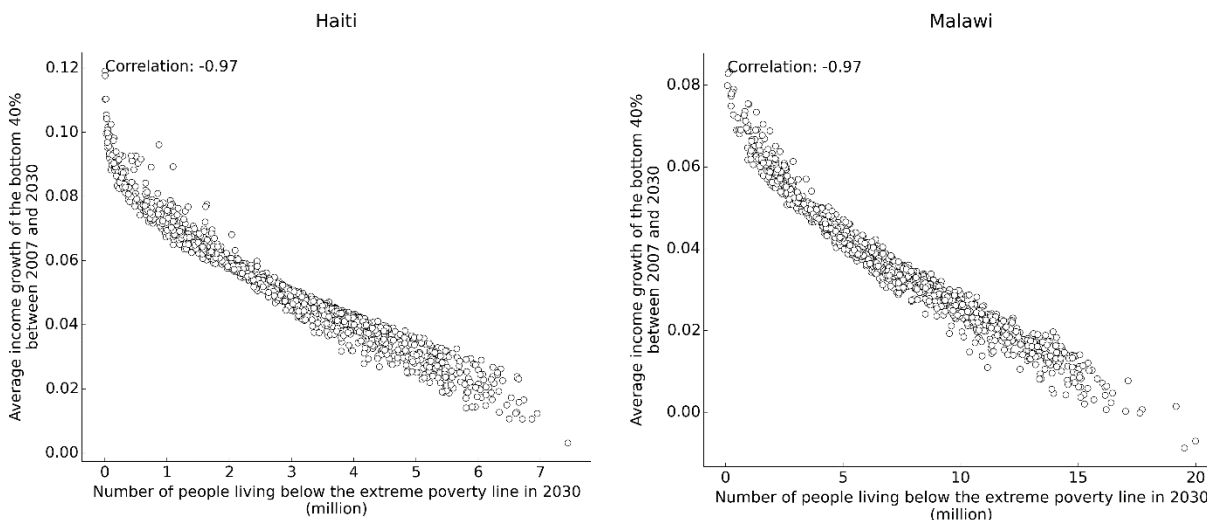
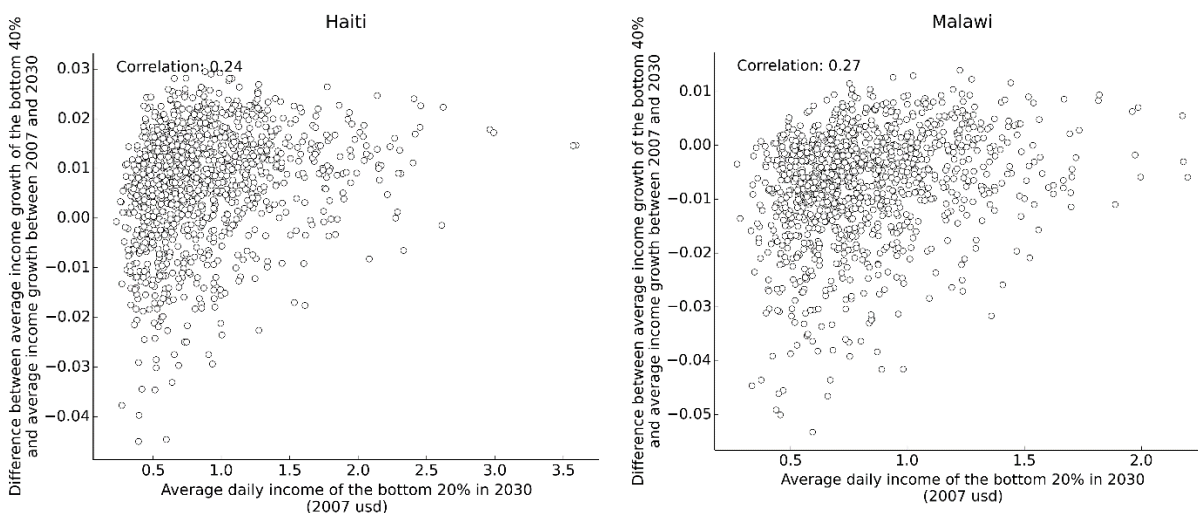


Figure 1: World Bank goals indicators for 1200 scenarios in 2030 for Haiti (left) and Malawi (right).

Figure 1 represents the correlation between the two World Bank twin goals: each dot shows the position of one scenario in 2030 for the selected country, with the horizontal axis representing the number of people living in extreme poverty and the vertical axis representing the average income growth of the bottom 40 percent. This high correlation suggests that the two goals of the World Bank are consistent, and do not imply specific trade-offs in terms of policy priorities.

The number of people living below the extreme poverty line is not easy to use when building scenarios for 2030 because the definition of absolute poverty is likely to evolve over time. For that reason, we focus on the average income of the bottom 20% in 2030 as an indicator for poverty.



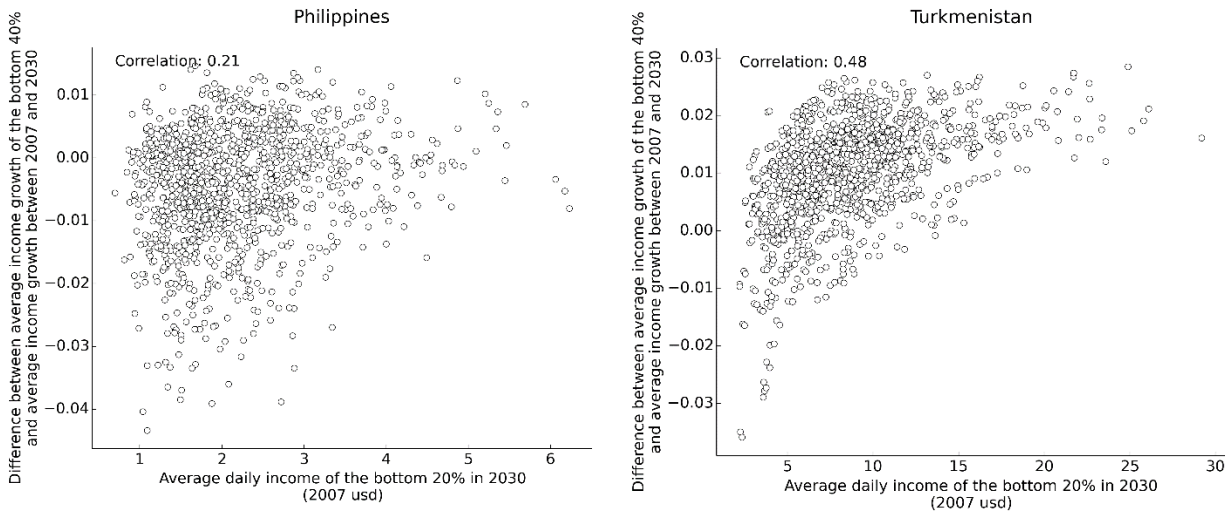


Figure 2: Chosen indicators for poverty and inequalities for four countries.

We complement this poverty indicator with an indicator for inequality. Here, we use the difference between the income growth of the bottom 40% and the average income growth in the country. If the bottom 40% is growing faster than the average, this difference is positive and inequality are likely to be reduced (theoretically, and depending on the inequality indicator, it also depends on what happens within the bottom 40 percent and within the top 60 percent). Figure 2 shows all scenarios (each represented by a dot) along the two indicators: the average income of the bottom 20% in 2030 (indicator for poverty) and the difference between the income growth of the bottom 40 percent and the average income growth (indicator for inequality).

As the figure shows, the correlation between poverty and inequality is low (between 0.21 and 0.48 in the four countries), although there is no scenario in the bottom-right corner of the graph, i.e. with an increase in inequalities but low poverty. It shows that inequality and poverty reduction are not driven by the same determinants, and that different policies will affect the two indicators. It also means that policy priorities will be different depending on whether the main goal is to reduce poverty or reduce inequality.

### 2.3. Range of possible futures and main drivers

Consistently with our goal of exploring the largest possible uncertainty, the range of income growth in our scenarios is much larger than the one explored in other scenario exercises, such as the SSPs (Figure 3). All the hypotheses that were made on the input parameters appear however possible (or at least, non-impossible) and based on historical data (see Appendix).

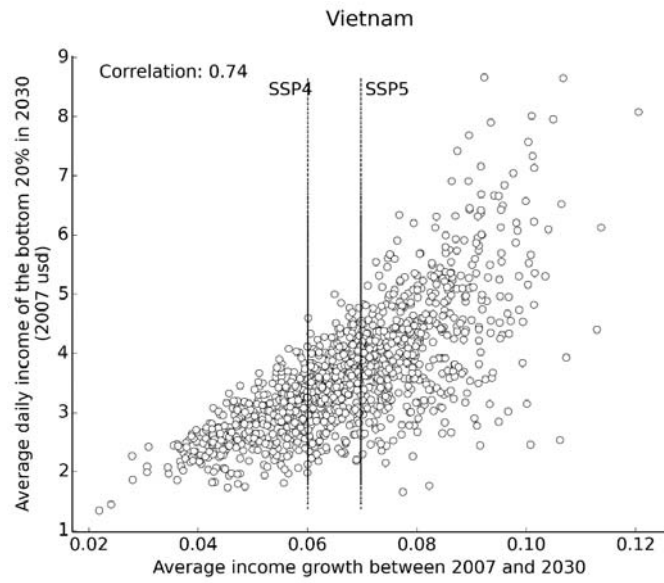


Figure 3 Uncertainty range on total income growth coming out of the experiment, and SSP growth for Vietnam in SSP4 and SSP5, represented by the two vertical lines.

To understand better the role of various drivers, Figure 4 and Figure 5 illustrate the impact of two input drivers on our two indicators in Sierra Leone. Figure 4 identifies in red the scenarios with high population growth and shows (left panel) that demography has a very strong impact on the income of the bottom 20%: all scenarios with high population growth have limited growth in consumption per capita, for the bottom 20 percent and for the entire population. In contrast, population has a much weaker impact on the inequalities indicator (right panel).

Figure 5 shows that for a given level of total income growth, redistribution maximizes the income of the bottom 20%, but it is not sufficient to guarantee a relatively high income for the poorest, especially in scenarios with slow aggregate growth. The shape of the scenario cloud emphasizes this result: there are no scenario with a large growth in the income of poor without a large aggregate growth. In other terms, aggregate growth is necessary to eradicate poverty in Sierra Leone and redistribution alone cannot achieve it; this result is consistent with empirical findings on the fact that “growth is good for the poor” (Dollar and Kraay 2002; Dollar, Kleineberg, and Kraay 2013; Ferreira and Ravallion 2008). In contrast, redistribution guarantees low inequalities because in all scenarios with high redistribution the income of the bottom 40% grows at least as fast as the average income.

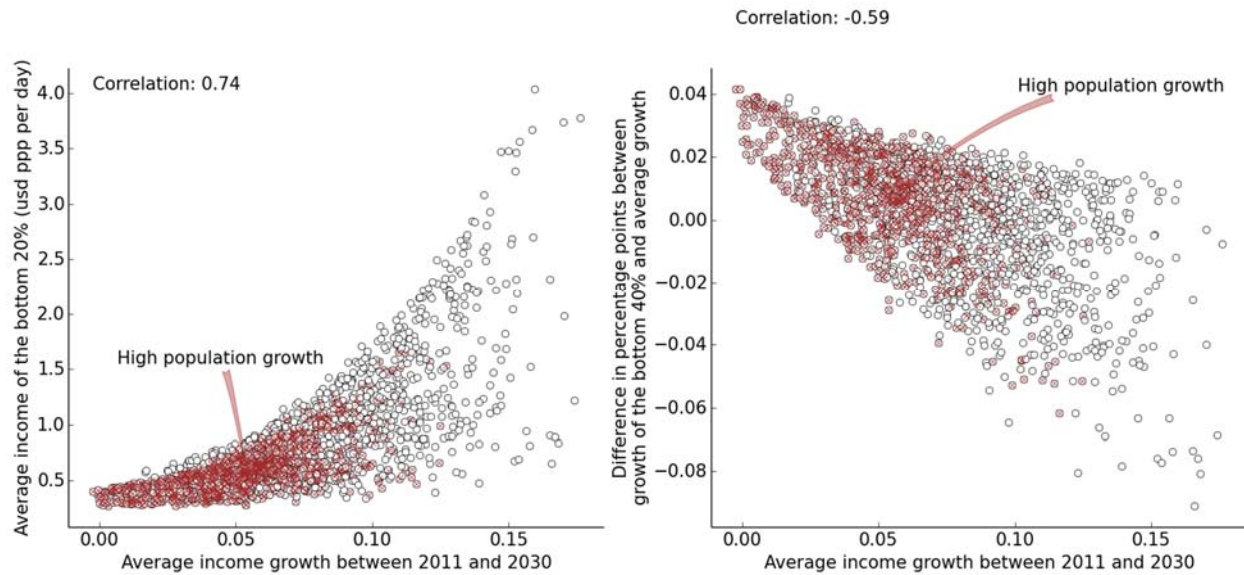


Figure 4 Impact of demography on the two indicators and on income growth in Sierra Leone.

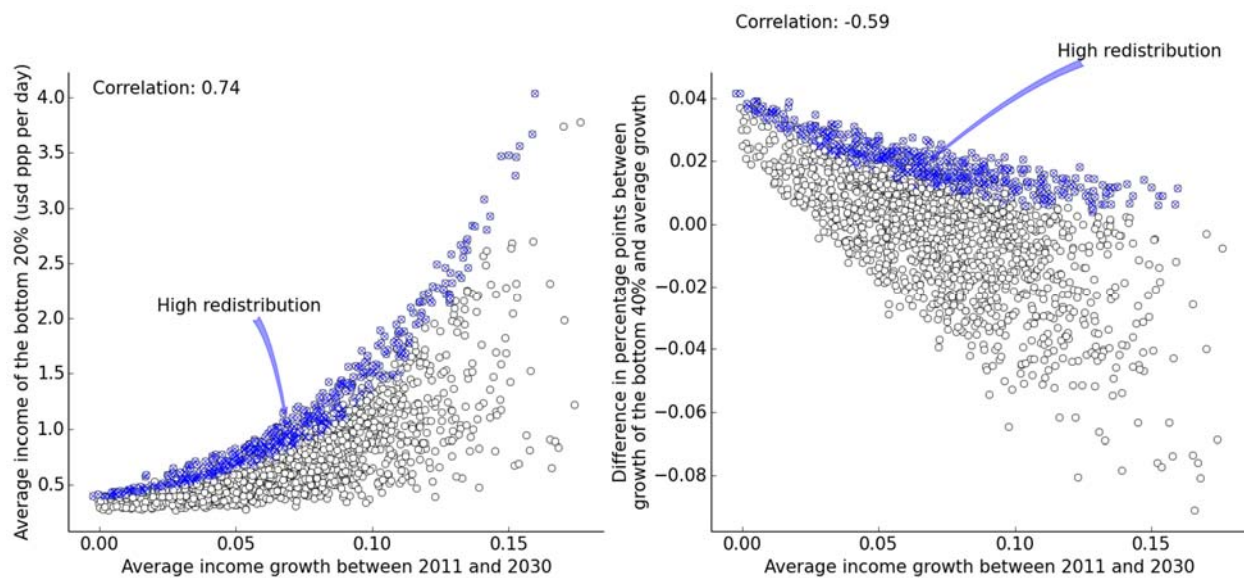


Figure 5 Impact of redistribution on the two indicators and on income growth in Sierra Leone.

### 3. What needs to happen to reduce extreme poverty?

To understand more systematically what input parameters drive the dispersion of poverty and inequalities, we perform two simple analyses of variance for our two indicators. The analysis of variance partitions the observed variance of a variable into components attributable to different sources of variation. In other words, we are explaining the variance of the outputs of our micro-simulation (income of the bottom 20% and income share of the bottom 40%) model by the variance of the inputs (the 12 sources of uncertainty identified previously).

Figure 6 illustrates the importance of various parameters to eradicate extreme poverty (as a result of the analysis of variance). The countries that are highlighted in the different panels are the countries where a given driver plays a large role in determining one indicator. For instance, panel (a) shows the countries where demographic changes represent an important driver of poverty reduction (in the sense that demographic trends explain a large part of the variance in poverty in 2030). In other terms, the level of poverty in 2030 is strongly influenced by demographic trends in the countries highlighted in the panel (a) of Figure 6. Panel (b) shows the same results for agricultural productivity and panel (c) for redistribution.

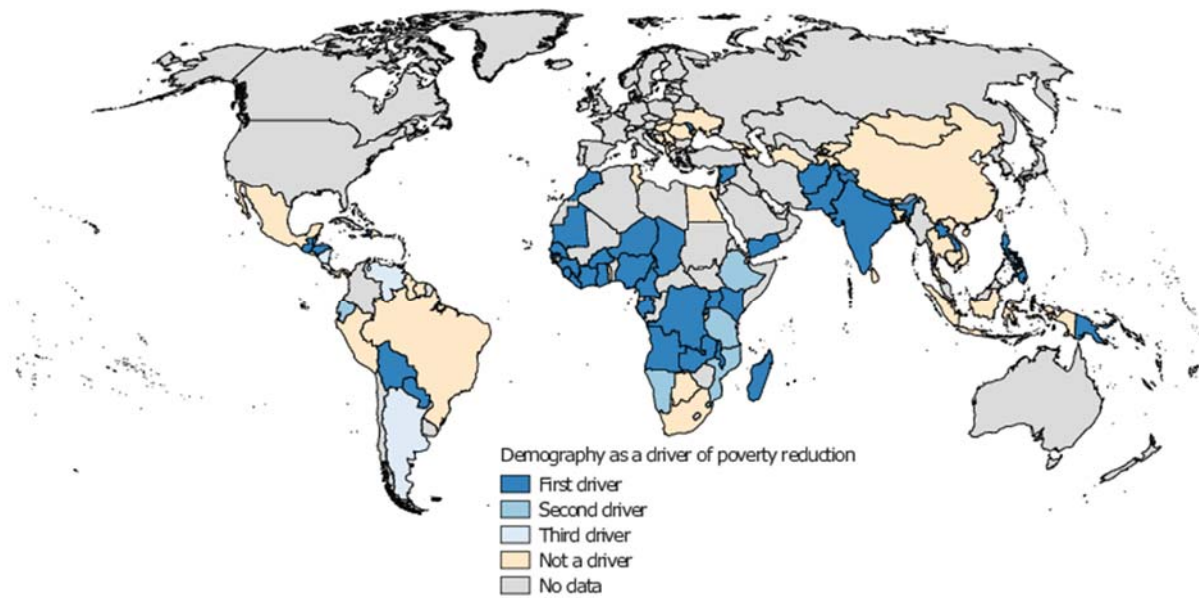
As shown in panel (a), population (demography and education) is a critical parameter in the majority of low-income countries: in short, eradicating poverty becomes extremely difficult in the scenarios with high population growth and low education levels. In the countries that are not highlighted in panel (a), eradicating poverty is possible regardless of the demographics scenario, and other drivers matter more. Unsurprisingly, most of Sub-Saharan Africa is in this situation where population growth is critical, suggesting also that family planning could be an important policy lever to reduce poverty. These results are consistent with (Gupta 2014; Ahmed et al. 2014), which agree that a smaller population growth will be an important driver of future economic growth and poverty reduction in low-income countries, especially in a context of climate change and pressure on natural resources (see also Lanjouw and Ravallion, 1995, on the role of household size).

Similarly, in the countries in green in panel (b), it is very difficult to eradicate extreme poverty in the absence of sufficient gains in agricultural productivity. In these countries, improvement in agricultural productivity (especially for the unskilled) is necessary to reduce poverty, suggesting that agricultural policy should be a priority. Twenty-seven countries are in this situation, especially in Sub-Saharan Africa and South Asia (e.g., Vietnam, Lao). This result parallels findings by (Lanjouw and Murgai 2009) who found that the income of unskilled agriculture workers was an important driver of poverty reduction in India in the 1980s and 1990s. It is also consistent with (Christiaensen, Demery, and Kuhl 2011) who find that agriculture is critical for reducing extreme poverty more than for improving the condition of the near-poor people (at \$4 and more). As we will see later, poverty reduction is particularly vulnerable to the impacts of climate change on agricultural production in these countries.

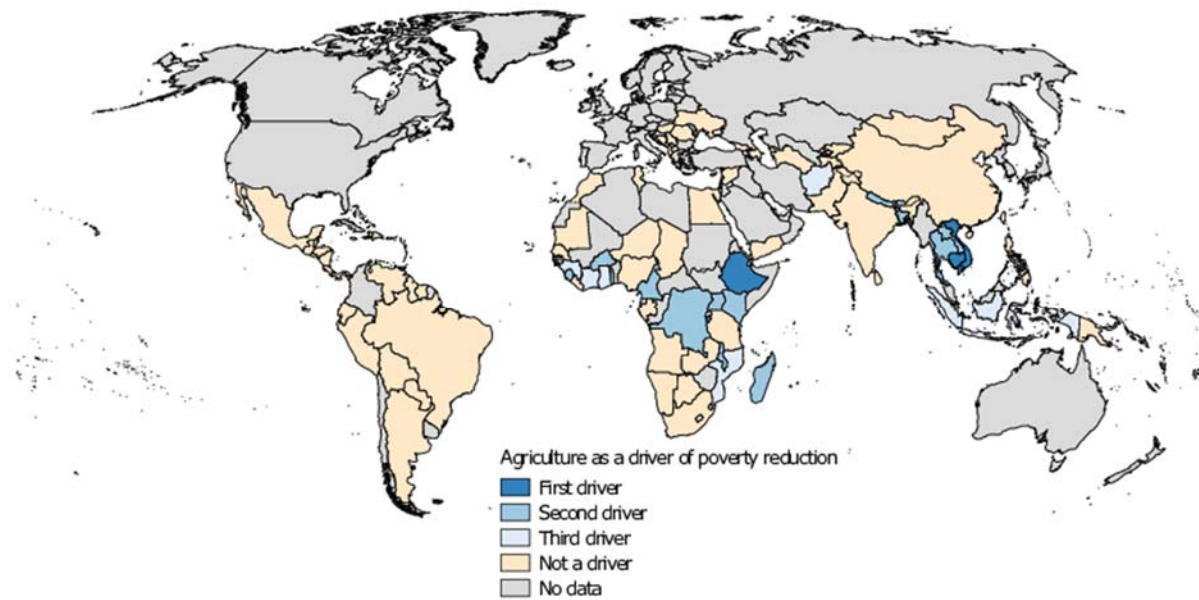
In the countries in blue in panel (c), income redistribution significantly helps reducing poverty. For instance, Brazil is one of the countries where redistribution is able to produce large reduction in poverty even in the absence of rapid growth, and indeed such a pattern was observed in the past (Ferreira, Leite, and Ravallion 2010). Unsurprisingly, countries where redistribution is efficient are mostly middle-income countries (Mexico, China), where the average income is high enough to make redistribution an efficient option to reduce poverty. In the poorest places, the average income is simply too low to make redistribution an efficient tool against poverty. (Ravallion 2010) finds that there is a cut-off point of about \$3,500 as an estimate of a level of income at which extreme poverty could be removed through redistribution by taxing the rich with incomes more than \$13 in PPP per day at reasonable marginal rates.



(a) demography



(b) agriculture productivity





(c) redistribution

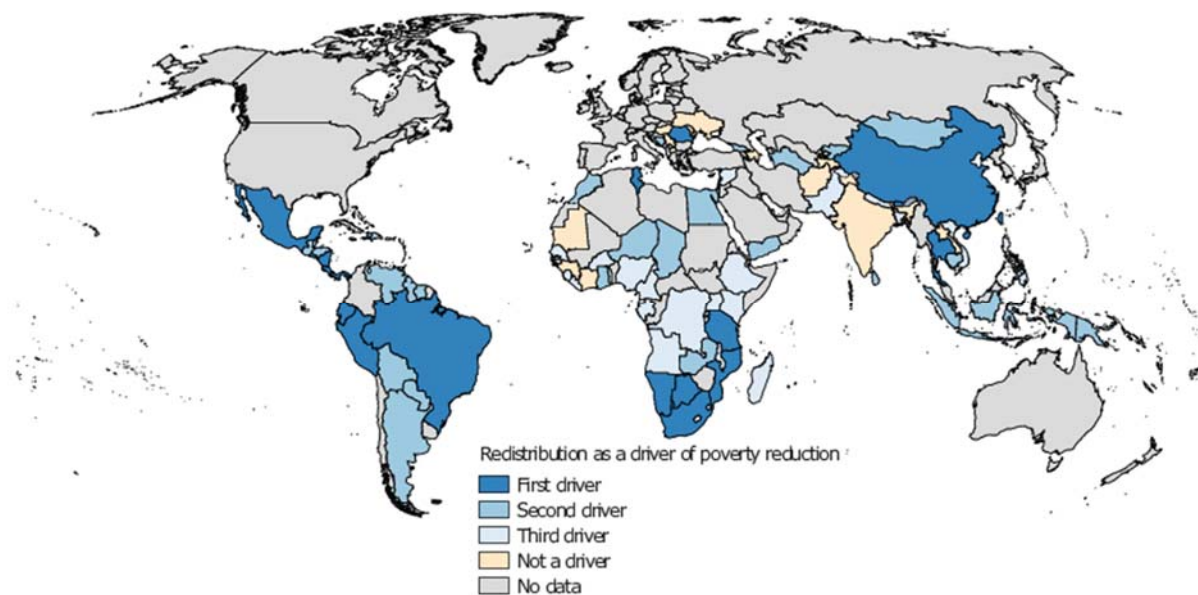


Figure 6 Countries where demography (panel a), agriculture productivity (panel b) and redistribution (panel c) are among the most important parameters for extreme poverty eradication.

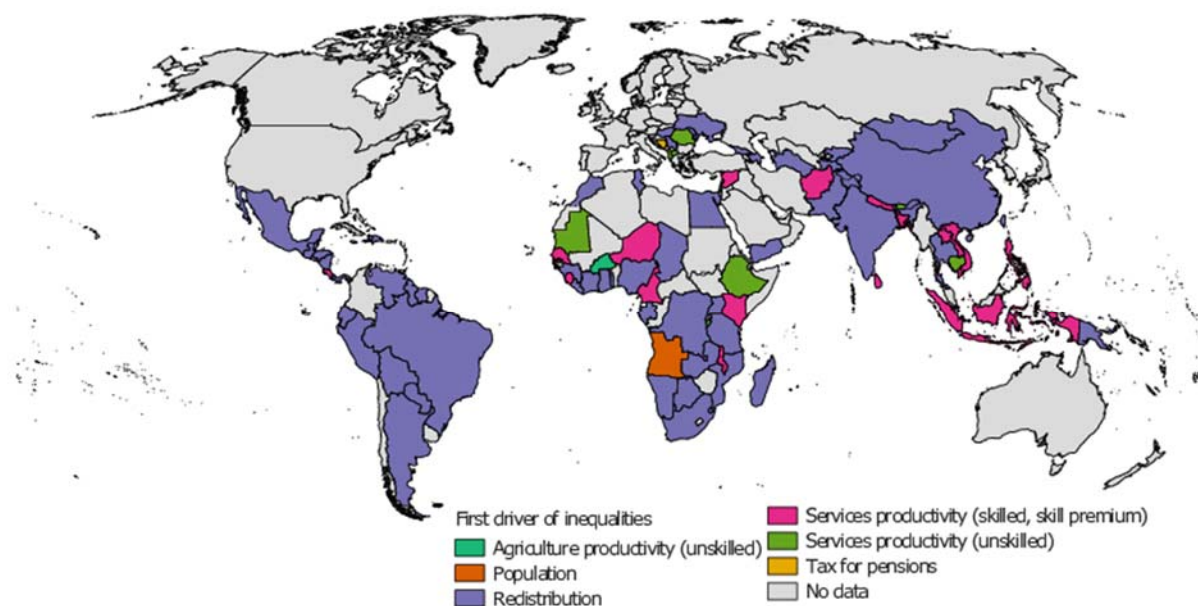


Figure 7 First driver of inequalities (difference between the income growth of the bottom 40% and the average income growth in each country)

Obviously, several drivers matter for poverty eradication in each country, but again the set of drivers varies across countries. In Ethiopia for instance, the first driver of poverty is agriculture productivity, the second driver is demography and the third driver is redistribution. In Ukraine or Azerbaijan, conversely,

none of those driver matter and poverty is instead driven by participation rates in the labor force and income growth in the service sector (for skilled and unskilled workers).

Figure 7 shows the first driver of inequalities for all countries. Welfare transfers (“redistribution”) is the main driver of inequalities for 61 countries and is one of the three main drivers in all countries. The second most important drivers are productivity growth for skilled and unskilled workers in services: the higher the growth for unskilled workers the lower the inequality, and the higher the growth for skilled workers, the higher the inequality. This result shows that future inequalities will depend on what happens in the service sector, and especially the balance between informal low-productivity services and modern services (Rodrik 2011).

#### 4. Identifying two representative scenarios: “prosperity” vs. “poverty”

In each country, we select two scenarios (among the hundreds per country) that are contrasted in terms of the main drivers of poverty and inequality indicators, and representative of the conditions in which poverty is reduced rapidly or more slowly.

In each country, we select a box of “optimistic” scenarios (in green in Figure 8 in the case of Vietnam) and a box of “pessimistic” scenarios (in purple in Figure 8). The scenarios are selected in terms of poverty and inequality only: optimistic scenarios are the ones above the median for both the average income of the bottom 20% and for difference in growth rates between the income of the bottom 40% and average income. Similarly, pessimistic scenarios are the ones below the median for both indicators.

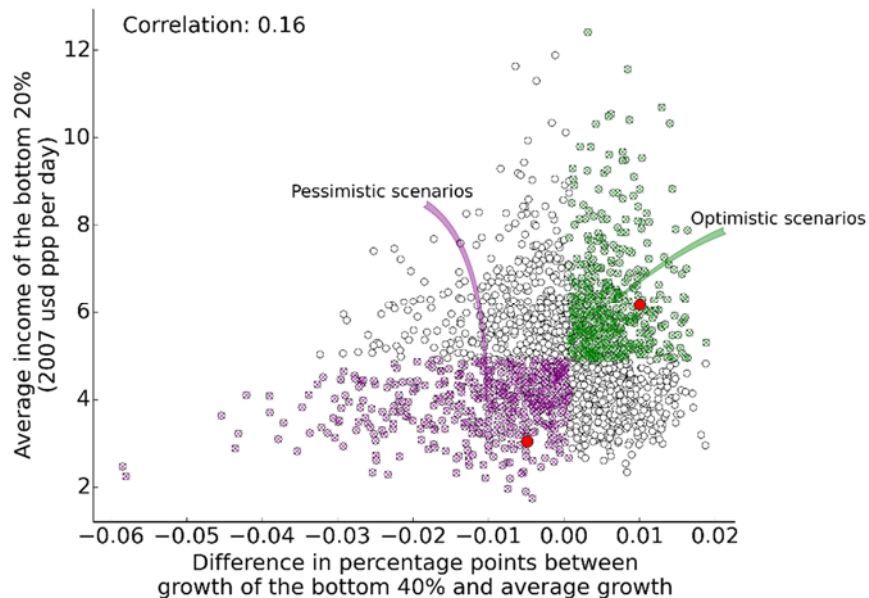


Figure 8 Selection of the optimistic and pessimistic boxes and of the two representative scenarios in Vietnam (two red dots).

We then use a scenario discovery algorithm<sup>6</sup> (Bryant and Lempert 2010) to identify a combination of input drivers that is most likely to put the scenario in the optimistic or pessimistic box. In other words, we identify the range of parameter values that are found in this subset of scenarios (we may find that the scenarios with lower poverty and lower inequality are typically those with low population: it means that most scenarios with lower poverty and lower inequality have also low population, and that most scenario with low population have also lower poverty and lower inequality). For instance, optimistic scenarios in Vietnam are mostly scenarios with high redistribution level, relatively high pension levels, low population growth and high education (SSP5 demography), and relatively high productivity growth for unskilled agricultural workers. Pessimistic scenarios are characterized by relatively low redistribution level, high population growth and low education (SSP4 demography), and low productivity growth for unskilled agricultural workers. The details are in Table 1. The other parameters (e.g., structural change or change in productivity in service or manufacturing) play only a secondary role.

*Table 1: sets of conditions that characterize the scenarios in the optimistic box (defined as in Figure 8) for Vietnam. Density is the probability of a scenario which matches the set of conditions to be in the optimistic box. Coverage is the probability of a scenario which is in the optimistic box to match the set of conditions.*

|  |   |
|--|---|
| <b>Optimistic set of conditions</b><br>78% density<br>40% coverage | <ul style="list-style-type: none"> <li>- High redistribution (tax for cash transfers &gt;8% of total consumption)</li> <li>- Relatively high pensions (tax &gt;5% of total consumption)</li> <li>- Low population growth, high education (SSP5)</li> <li>- Productivity growth for unskilled agriculture workers &gt;2% per year</li> </ul> |
|--|---|

*Table 2: drivers for the scenarios in the pessimistic box (defined as in Figure 8) for Vietnam. Density is the probability of a scenario which matches the set of conditions to be in the optimistic box. Coverage is the probability of a scenario which is in the optimistic box to match the set of conditions.*

|   |   |
|---|---|
| <b>Pessimistic set of conditions</b><br>47% density<br>59% coverage | <ul style="list-style-type: none"> <li>- Relatively low redistribution tax for cash transfers &lt;15% of total consumption)</li> <li>- High population growth, low education (SSP4)</li> <li>- Productivity growth for unskilled agriculture workers &lt;5% per year</li> </ul> |
|---|---|

To select one representative scenario in each box, we select only scenarios that correspond to the main set of drivers and apply the following additional criteria. For the pessimistic scenario we selected a scenario with a total income growth that is close to GDP growth in the SSP4 (the SSP scenario in which poverty and inequality remain high) and minimized structure change (to represent stagnation). For the optimistic scenario, we selected a scenario with a total income growth that is close to GDP growth in the SSP5 (the SSP scenario with the largest GDP growth), while minimizing the share of workers in agriculture, maximizing the share of workers in industry, and making sure that skill premiums are not too different between sectors.

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<sup>6</sup> Here we use the EMA work bench developed at Delft University: <http://simulation.tbm.tudelft.nl/ema-workbench/contents.html>

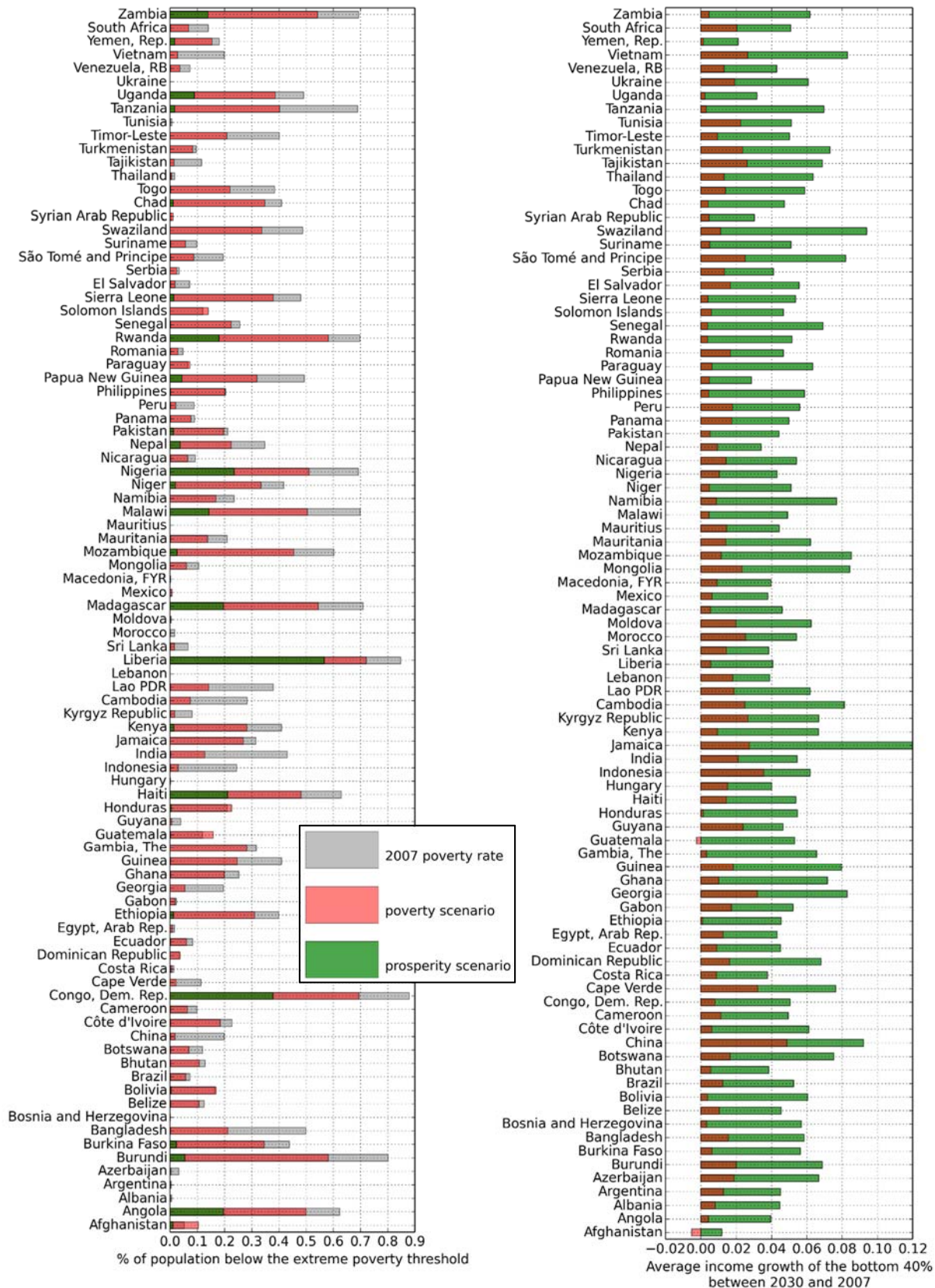


Figure 9 Poverty rates (left) and income growth of the bottom 40% (right) in the optimistic (prosperity) and pessimistic (poverty) scenarios, for the countries of the I2D2 database

We then aggregate all optimistic country-level scenarios into a global optimistic scenario, labelled the *prosperity* scenario. This scenario is consistent with the World Bank twin goals of eradicating extreme poverty and promoting share prosperity: (1) the number of people living below the extreme poverty line is less than 3% of the global population; and (2) consumption growth for the bottom 40% in countries is high. We also assume that the world described in our prosperity scenario provides basic services (electricity, water and sanitation), basic social protection, and health care and coverage to the entire population. Since each country-level scenario is chosen so that GDP growth is close to the GDP values from the SSP5 and that most countries optimistic scenario have the demographics from the SSP5, our *prosperity* scenario can be considered as a quantified pathway for poverty in the SSP5. But our *prosperity* scenario is not the SSP5, and it does not follow the narrative from the SSP5, especially concerning the energy mix and use of fossil fuels.

Similarly, we aggregate all pessimistic country-level scenarios into a global pessimistic scenario, labelled the *poverty* scenario. In this scenario, extreme poverty decreases much less, to reach 11% of the global population in 2030, inequality is much larger across and within countries. In this scenario, we also assume that access to basic services, social protection, and health care improves only marginally. This scenario is consistent with the narrative from the SSP4, and our *poverty* scenario can therefore be considered a quantification of poverty in SSP4.

Figure 9 shows the poverty rate (left panel) and income growth of the bottom 40 percent (right panel) in all countries, in 2007 and in 2030 in the poverty and prosperity scenarios. These two scenarios are representative of successful futures and more pessimistic ones, and can be used to assess the consequence of various shocks and stresses, accounting for the different in vulnerability due to future socioeconomic trends.

It is important to note that these scenarios are not extreme scenarios and they do not provide a range of what is considered possible or plausible: instead, they represent typical scenarios for two possible future, one optimistic and one pessimistic. But it is possible to find in our scenario set some scenarios that are better than the *prosperity* scenario or worse than the *poverty* scenario.

## 5. Climate change impacts on poverty

In each country and for each of the two selected socio-economic scenarios (*prosperity* and *poverty*) we introduce climate change impacts on food price and production, health, labor productivity, and natural disasters. We add these climate change impacts to the characteristics of each household in the database, following the methodology described in Section 2.

The climate change impacts are not “new” impacts: they mostly correspond to the worsening of existing issues, such as more frequent disasters or more malaria cases. In this analysis, we assume that the impacts due to the current climate are already included in our baseline scenarios, *prosperity* and *poverty*. We add to these scenarios the *additional* impact of climate change. For malaria for instance, the current extent and impacts of the disease are assumed already included in the scenarios presented in Section 4, and we add the costs and lost income from the cases that would not have occurred in the absence of climate change.



It remains out of reach to include all possible impacts in such an analysis, so we considered only the channels through which climate change is most likely to affect poverty reduction. We focus on direct impact on poverty – e.g. through health – and do not focus on the impact of climate change on aggregate growth, at the macroeconomic level, and the secondary impact on poverty reduction. This is a limitation considering the evidence that aggregate growth is a major driver of poverty reduction (Dollar and Kraay 2002; Dollar, Kleineberg, and Kraay 2013). We do so because previous research suggests that the macroeconomic impact of climate change are likely to remain limited by 2030 (Arent et al. 2014; Stern 2006), and because we hypothesize that the main channel from climate change impact to poverty are the direct impacts, that are invisible in macroeconomic models (Hallegatte et al. 2014).

### 5.1. Sectoral impacts on households

In each country and for each of the two selected socioeconomic scenarios (*prosperity* and *poverty*) we introduce climate change impacts on food price and production, natural disasters, and health. In the projections of the 1.4 million households modeled in our scenarios (representing 1.2 billion households), we adjust the income and prices to reflect the impact of climate change on their ability to consume, and derive the impact on poverty.

Given that the sector-level impacts are highly uncertain, we also define a *low-impact* and a *high-impact* scenario. These depend on the magnitude of the physical and biological impacts of climate change (which depend on the ability of ecosystems to adapt and on the responsiveness of physical systems such as glaciers and coastal zones) and on spontaneous adaptation in various sectors (such as adoption of new agricultural practices or improved hygiene habits). Note that with a 2030 horizon, impacts barely depend on emissions between 2015 and 2030, which only affect the magnitude of climate change over the longer-term, beyond 2050.

There are several limits to our approach. First, we follow a bottom-up approach and sum the sectoral impacts, assuming they do not interact. Second, we consider only a subset of impacts, even within our three sectors—for instance, we do not include the loss of ecosystem services and the nutritional quality of food. Third, we cannot assess the poverty impact everywhere. Our household database represents only 83 percent of the population in the developing world. Some highly vulnerable countries (such as small islands) cannot be included in the analysis because of data limitations, in spite of the large effects that climate change could have on their poverty rates.

#### Food prices and food production

The vulnerability of poverty reduction to food price hikes have already been demonstrated, for instance in (Ivanic and Martin 2008; Ivanic, Martin, and Zaman 2012; Hertel, Burke, and Lobell 2010; Devarajan et al. 2013). Impacts of climate change on agriculture affect poverty in two ways (Porter et al. 2014). First, an increase in food prices reduces households' available income, but especially consumption of the poor who spend a large share of their income on food products. The impact in our scenarios depend on the fraction of food expenditure in total expenditure, which decreases with the income level of the household (Figure 10). Food price changes also affect the farmers' incomes. However, this channel is complex since lower yields mean that higher food prices do not necessarily translate into more farmers' revenues: the net effect depends on the balance between changes in prices and quantities produced.

Food prices and production come from a global agricultural model (Havlík et al. 2015). They are different for each climate model considered, region, and global socio-economic scenario. We assume that food prices and productions follow the SSP5 path in our *prosperity* scenario and the SSP4 path in our *poverty* scenario. Then, for each region and in each scenario, we take the minimum and maximum price increase across all climate models (Global Climate Models or GCMs) and use them as boundaries to create an ensemble of scenarios (Table 3). We use the corresponding production variations to calculate the impact on farmers' income (ensuring that our price and production inputs are fully consistent).

Table 3 Low-impact and high-impact changes in the agriculture sector due to climate change (RCP8.5) in 2030. Source: GLOBIOM model (IIASA). Bold numbers are positive ones.

(a) Low-impact climate change

| World Bank region | SSP  | Socio-economic scenario | Price difference (minimum across all GCMs) | Corresponding production difference | Corresponding revenue difference |
|-------------------|------|-------------------------|--|-------------------------------------|----------------------------------|
| EAP               | SSP4 | Poverty                 | <b>0.37%</b>                               | -0.74%                              | -0.38%                           |
| EAP               | SSP5 | Prosperity              | -0.13%                                     | -0.75%                              | -0.88%                           |
| ECA               | SSP4 | Poverty                 | -2.62%                                     | <b>2.66%</b>                        | -0.024%                          |
| ECA               | SSP5 | Prosperity              | -3.27%                                     | <b>12.00%</b>                       | <b>8.34%</b>                     |
| LAC               | SSP4 | Poverty                 | <b>0.39%</b>                               | -0.21%                              | <b>0.18%</b>                     |
| LAC               | SSP5 | Prosperity              | -0.01%                                     | -0.18%                              | -0.19%                           |
| MNA               | SSP4 | Poverty                 | -2.03%                                     | <b>4.25%</b>                        | <b>2.14%</b>                     |
| MNA               | SSP5 | Prosperity              | -1.49%                                     | <b>1.70%</b>                        | <b>0.18%</b>                     |
| SAS               | SSP4 | Poverty                 | <b>3.29%</b>                               | -1.23%                              | <b>2.02%</b>                     |
| SAS               | SSP5 | Prosperity              | <b>1.46%</b>                               | -1.34%                              | <b>0.10%</b>                     |
| SSA               | SSP4 | Poverty                 | <b>0.74%</b>                               | -1.39%                              | -0.66%                           |
| SSA               | SSP5 | Prosperity              | <b>0.23%</b>                               | -1.33%                              | -1.10%                           |

(b) High-impact climate change

| World Bank region | SSP  | Socio-economic scenario | Price difference (maximum across all GCMs) | Corresponding production difference | Corresponding revenue difference |
|-------------------|------|-------------------------|--|-------------------------------------|----------------------------------|
| EAP               | SSP4 | Poverty                 | <b>3.4%</b>                                | -3.2%                               | <b>0.05%</b>                     |
| EAP               | SSP5 | Prosperity              | <b>1.9%</b>                                | -3.0%                               | -1.17%                           |
| ECA               | SSP4 | Poverty                 | -0.1%                                      | <b>0.9%</b>                         | <b>0.81%</b>                     |
| ECA               | SSP5 | Prosperity              | -1.0%                                      | <b>4.7%</b>                         | <b>3.72%</b>                     |
| LAC               | SSP4 | Poverty                 | <b>1.4%</b>                                | <b>0.2%</b>                         | <b>1.63%</b>                     |
| LAC               | SSP5 | Prosperity              | <b>2.0%</b>                                | <b>2.2%</b>                         | <b>4.26%</b>                     |
| MNA               | SSP4 | Poverty                 | <b>2.7%</b>                                | <b>0.5%</b>                         | <b>3.18%</b>                     |
| MNA               | SSP5 | Prosperity              | -0.8%                                      | <b>0.9%</b>                         | <b>0.14%</b>                     |
| SAS               | SSP4 | Poverty                 | <b>7.7%</b>                                | -4.5%                               | <b>2.85%</b>                     |
| SAS               | SSP5 | Prosperity              | <b>4.9%</b>                                | -3.5%                               | <b>1.22%</b>                     |
| SSA               | SSP4 | Poverty                 | <b>7.1%</b>                                | -6.1%                               | <b>0.63%</b>                     |
| SSA               | SSP5 | Prosperity              | <b>3.1%</b>                                | -5.8%                               | -2.91%                           |

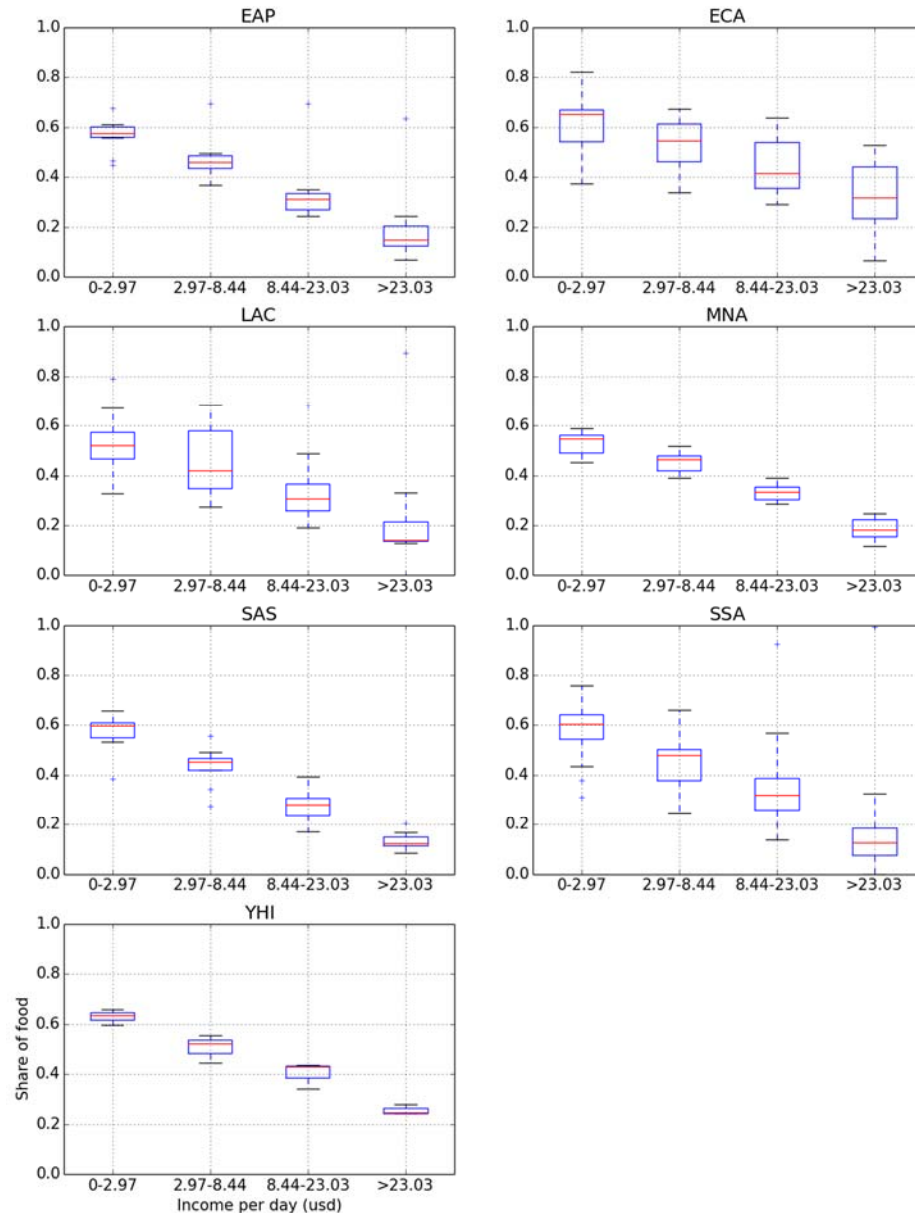


Figure 10 Share of food in total consumption, for each World Bank region and different income categories. Source: The World Bank Global Consumption Database.

Whether higher agriculture revenues (if the increase in price dominates the decrease in yield) are transmitted to poor farmers depends on how the benefits are distributed between farm laborers and landowners (see an example on Bangladesh in Jacoby, Rabassa, and Skoufias 2014). To account for these effects, we assume that the increase in agriculture revenues is entirely transmitted to agriculture workers in the *prosperity* scenario (due to favorable balance of power in labor markets), but that only 50% is transmitted in the *poverty* scenario, the rest being captured by land owners and intermediaries in the food supply chain (who are assumed rich enough not to affect our poverty estimates).



In practice, we change the income of all workers in the agricultural sector, according the “revenue difference” column in Table 3. We also rescale the (real) income of all households according to the change in food prices (“price difference” column in Table 3), accounting for the share of food in household budget (which decreases with income, see Figure 10). The impact of the agriculture channel on poverty depends on the number of farmers in each country, the income of these farmers, and the income of the entire population (which affects the share of food in consumption).

In the high-impact scenario, the number of people living below the extreme poverty line in 2030 increases by 67 million people in the *poverty* scenario because of climate change impacts on agriculture, and by 6.3 million people in the *prosperity* scenario. On average, therefore, the negative impact of climate change on food prices dominates the potential positive impacts through agriculture revenues.

## Health

We now include a set of additional impacts of climate change on health (stunting, malaria, and diarrhea).

### Stunting

Stunting is linked to malnutrition and therefore to food price, but acts through a different channel than the direct impact on food prices on the ability to consume. It is also driven by more than access to and affordability of food (Lloyd, Kovats, and Chalabi 2011; Hales et al. 2014). Socioeconomic characteristics such as parents’ education and access to basic services (especially improved drinking water and sanitation) also play a key role.

Stunting has short- and long-term impacts particularly for children younger than two. For instance, households reducing nutrition after droughts permanently lowered children stature by 2.3 to 3 cm (Dercon and Porter 2014; Alderman, Hoddinott, and Kinsey 2006). Hoddinott (2006) also observes the body mass index (BMI) of women reduced 3%; while this recovered the following year, impacts on children are long-lasting. Stunting is also linked to delayed motor development, lower IQ, more behavioral problems, lower educational achievement (less years of schooling), and reduced economic activity (Martorell 1999; Victoria *et al.* 2008; Currie 2009; Caruso 2015). These consequences have impacts on lifelong earning capacity and ability to escape poverty. In Zimbabwe, children affected by droughts had 14% lower lifetime earnings (Alderman et al., 2006) and in Ethiopia income was reduced by 3% for individuals who were younger than 3 years old during droughts.

Lloyd et al (2011) suggest that climate change could have a large impact on stunting, and even that climate change could dominate the positive effect of development in some regions, leading to an absolute increase in stunting over time. In our model, we use the ranges given in (Hales et al. 2014, Table 7.4) for the additional share of children estimated to be stunted because of climate change in 2030. To account for development, we investigate the distribution of stunting today using DHS household surveys. We find that prevalence of stunting drops for families whose income is above \$8,000 per year (Figure 11).

We randomly select a fraction of the households with income below \$8,000, so that stunting prevalence is consistent with data for the current situation. Then, we increase this fraction by the fraction given in (Hales et al. 2014, Table 7.4) to account for climate change. We assume that stunted individuals have

lifelong earning reduced by 5% and 15% in the low-impact and high-impact scenarios, respectively (regardless of their employment sector and skill level).

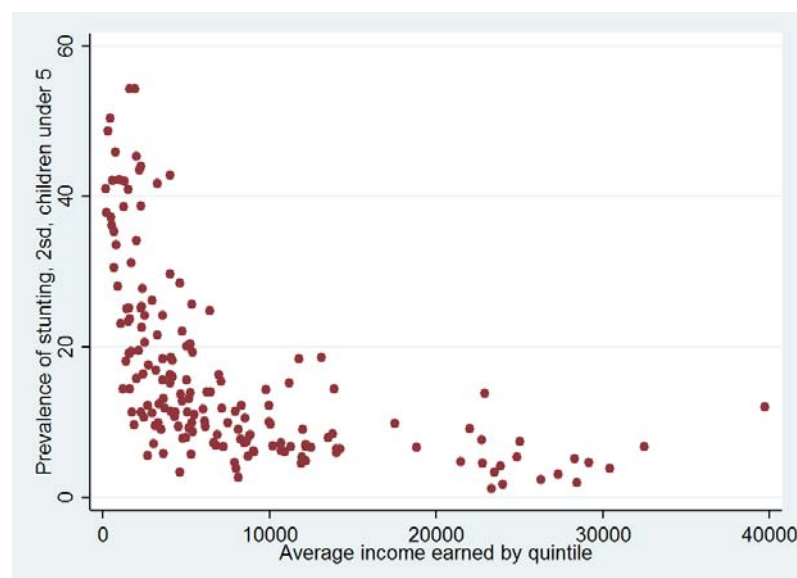


Figure 11 Prevalence of stunting for children under 5 (DHS data)

### Malaria

Climate change threatens to reverse the progress that has been made to date in the fight against malaria. It is difficult to identify what portion of malaria incidence can be attributed today to climate change but the World Health Report estimated climatic factors to be responsible for 6 percent of malaria cases (WHO 2002). Further, even small temperature increases could have a great effect on transmission of malaria. At the global level, increases of 2 or 3 degrees centigrade could increase the number of people at risk for malaria by up to 5 percent – representing several million. Malaria could increase by 5-7 percent in populations at risk in higher altitudes in Africa, leading to an increase in the number of cases by up to 28 percent (Small et al 2003; Tanger et al 2003).

In our scenarios, we use results from (Caminade et al. 2014), which give the percentage increase in malaria cases in 2030, in each country, due to climate change. To account for uncertainty in prevalence, we assume that the number of occurrence per year for the people affected by malaria will be between 0.1 and 2 (in reality, this number will depend on the places that are affected, the type of malaria, the health condition of the population, and the available treatments and health care).

Malaria is not always deadly but is a debilitating disease that often results in recurring bouts of illness (Cole and Neumayer 2006). In this analysis, it is assumed that malaria has impacts through the cost of treatment (between \$0.7 and \$6 per occurrence) and lost days of work (directly or to care for someone else). We use the ranges in Table 4 extracted from (Attanasio and Székely 1999; Konradsen et al. 1997; Ettling et al. 1994; Louis et al. 1992; Desfontaine et al. 1989; Desfontaine et al. 1990; Guiguemde et al. 1994).

Like for stunting, we randomly select individuals that are affected by malaria, based on current prevalence and estimates of future change due to climate change in various world regions from (Caminade et al. 2014). Then, we assume that these people are affected between 0.1 and 2 times per year, and lose income as presented in Table 4.

*Table 4 Malaria impacts on households in our model*

|                                | Min impact | Max impact |
|--------------------------------|------------|------------|
| Cost of treatment              | \$0.7      | \$6        |
| Number of days out of work     | 1          | 5          |
| Number of occurrences per year | 0.1        | 2          |

### *Diarrhea*

As the third leading cause of death in low-income countries, diarrhea is an important risk for poor households due to easy contamination pathways resulting from unsatisfactory hygiene conditions and high exposure (WHO 2008). Reduction in diarrhea incidence may be undermined by climate impacts that damage urban infrastructure and reduce the overall availability of water through water resource depletion.

Here we use data by (Hutton, Haller, and others 2004) for the number of cases per country today and the cost of treatment (Table 5). According to (Kolstad and Johansson 2010) the prevalence of diarrhea could increase by 10% by 2030 because of climate change (in all regions), and we use this assessment in our scenarios.

*Table 5 Diarrhea impacts on households in our model*

|  | Low-impact scenario | High-impact scenario |
|--|---------------------|----------------------|
| Cost of treatment                                | \$2                 | \$4                  |
| Days out of work (for the sick or the caregiver) | 3                   | 7                    |
| Number of occurrences per year                   | 1                   | 8                    |

To account for development, as for stunting, we use DHS data to explore the relationship between the income of the households and its exposure to diarrhea (Figure 12). These data do not show a dramatic decrease with income and diarrhea persists at high income levels. In practice, we use a 10 percent prevalence as a reference level, beyond which diarrhea has economic impacts, and we use a linear regression to estimate the income level at which prevalence decreases below 10 percent. We find a threshold at \$15,600 per year, and we assume that only households with income below this level are affected by the climate change effect on diarrhea.

Further, we assume that fast progress in access to water and sanitation in the *prosperity* scenario halve the number of cases, consistently with the assessment in India by (Andres et al. 2014). Of course, this assumes that the new water and sanitation infrastructure are adapted to changing future climate conditions and can continue to perform well in 2030 and beyond. This would require to account for the

uncertain in climate projections in the design phase, and to invest in the additional cost of more resilient infrastructure, possibly factoring in safety margins and retrofit options (Kalra, Gill, et al. 2014).

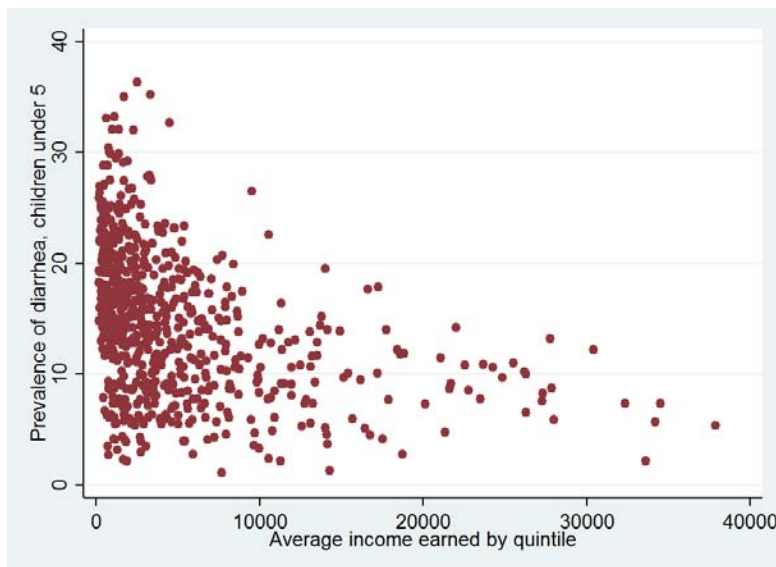


Figure 12 Prevalence of diarrhea in the past 2 weeks (DHS data)

In practice, we select randomly individuals in households with income below \$15,600 so that the number of case match data for the current situation. Then, we change the fraction of affected people to account for climate change using (Kolstad and Johansson 2010). For the affected people because of climate change, we reduce their income using estimates of the cost of treatment and lost income.

Overall, worst case health impacts of climate change put 28 million people back into poverty in 2030 in the *poverty* scenario and 4.1 million people in the *prosperity* scenario. The impact is smaller than that of agriculture for both scenarios, but remain noticeable.

### Temperature and labor productivity.

Recent studies suggest that there is a significant impact of temperature stress on labor productivity, which may be exacerbated by global climate change (Dell, Jones, Olken, 2014). In particular, there are direct physiological effects of thermal stress on the human body, which may affect productivity and labor supply, especially in developing countries (Heal and Park, 2015). Using variations in weather, several studies identified a relationship between extreme temperature – for instance, hotter-than-average years or extremely hot days – and economic outcomes such as labor productivity (Hsiang, 2011; Sudarshan et al, 2014; Dell, Jones, Olken, 2014).

For instance, Niemelä et al. (2002) find that, above 22 degrees C, each additional degree C is associated with a reduction of 1.8 percent in labor productivity for call center workers. Adhvaryu et al (2013) and Sudarshan et al (2014) find similar results in the manufacturing sector, with worker efficiency at the plant level declining on hotter days, even after controlling for absenteeism. In Sudarshan et al (2014), days above 25 degrees C reduce productivity in manufacturing plants by about 2.8% per degree C. Reviewing experimental studies, Seppanen, Fisk et al. (2006) find that the average productivity loss from

temperatures above 25°C is on the order of 2% per degree C. Figure 13 suggests the existence of an optimal temperature for economic activity, based on an analysis of non-agricultural payroll in US counties between 1986 and 2012 (Park 2015).

Today, temperatures are about 1C higher than they would be in the absence of climate change. In 2030, the difference will be around 1.2 or 1.4C. In our analysis, we assume that that people working outside or without air conditioning will lose between 1 and 3% in labor productivity due to this change of climate, compared with a baseline with no climate change. To assess the number of people affected, we use the shares of people working outside or without air conditioning in Table 6. We select randomly a number of workers who are supposed to work outside or without air conditioning according to the fraction in Table 6, and we reduce their income by 1 to 3%.

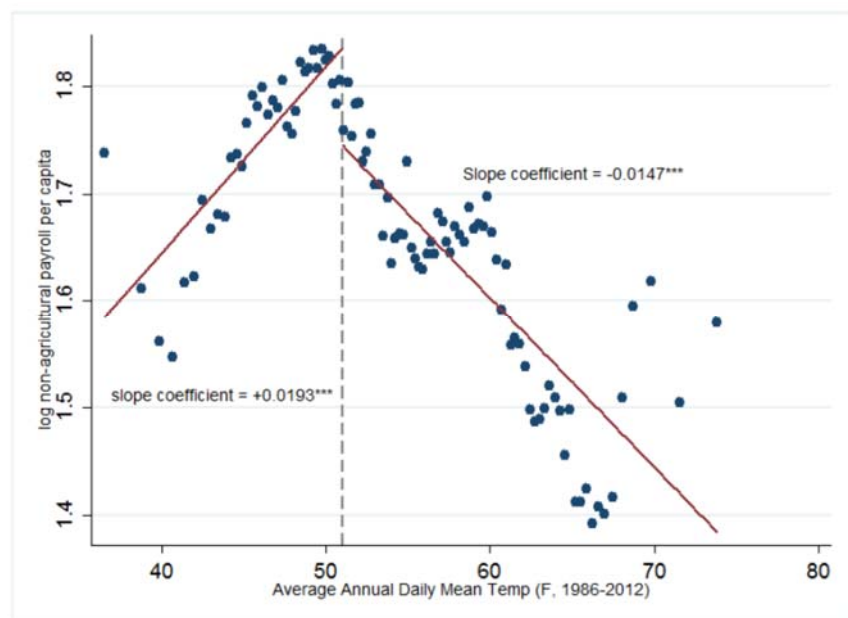


Figure 13. An optimal temperature zone for economic activity? Non-agricultural payroll and average annual temperature in US counties (by percentile). Source: Park (2015)

Table 6 Share of people working outside or without air conditioning

| Share of people working outside or without air conditioning | National income below \$10,000 per capita | National income above \$10,000 per capita |
|---|---|---|
| Agriculture   | 0.8                                       | 0.8                                       |
| Manufacture   | 0.5                                       | 0.1                                       |
| Services  | 0.3                                       | 0.05                                      |

We find that with high climate change impacts, 19 million people would fall back into poverty in 2030 in the *poverty* scenario and 2.7 million people in the *prosperity* scenario because of the impact of temperature.

## Natural disasters

For natural disasters, we work based on orders of magnitude using the EM-DAT database, and focus on direct economic losses, disregarding human losses and indirect and second-order losses (Hallegatte 2014; Hallegatte 2012). We start from current economic losses due to natural disasters, which have evolved between \$50 and \$200 billion in recent years, i.e. between 0.05 and 0.2 percent of the world GDP.

Defining the affected population is very difficult. Here we use the people who are directly and negatively affected by disasters, and suffer from significant loss of income. We estimate that the number of directly affected people is between 0.2 and 3 percent of the world population, i.e. between 15 and 200 million person per year. We use a “best guess” of 100 million affected people per year (1.4% of the world population).

We assume that the disasters in the no climate change scenarios are already included in the baseline socio-economic scenario, and we add to our simulations the additional disaster losses due to climate change. We make crude assumptions on how climate change will affect disaster losses, reflecting the large uncertainty on the effect of climate change on extreme events and the fact that losses will be highly dependent on how protections and other adaptation measures change over time.

We know that economic losses from natural disasters are expected to increase due to climate change, and that the increase could be rapid if appropriate adaptation measures are not implemented (see a review in IPCC 2014). Hallegatte et al. (2013) show for instance that in coastal cities, floods will increase very rapidly if protections are not upgraded regularly to account for sea level rise.

Here, we assume that the fraction of the population that will be affected annually by a disaster increases from an average today around 1.4 percent of the world population to 2 percent in the low-impact case and 3 percent in the high-impact case. It means that between 0.6% and 1.6% of the world population would be affected by natural disasters because of climate change and in addition to the baseline risk without climate change. These numbers will depend on how effective and timely adaptation to new climate conditions is, so that these two assumptions can be considered as two assumption on adaptation performance. Further research will be needed to refine these numbers and link them to explicit assumptions regarding the adaptation process.

We assume that poor and non-poor people are as exposed to natural disasters, consistently with the global average in (Winsemius et al. 2015), even though a bias with more poor people being exposed to disasters is observed in some countries, and in most local-scale studies.

In the low-impact case, we assume that affected people lose 20 percent or 10 percent of their annual income, depending on whether they are poor or non-poor. In the high-impact case, we assume that they lose 30 percent or 15 percent of their annual income, depending on whether they are poor or non-poor. These numbers are in line with post-disaster household surveys, even though much higher values are sometimes observed (Patankar 2015; Patankar and Patwardhan 2014; Noy and Patel 2014; Carter et al. 2007).

Here, we assume that disasters affect income only for the year when they occur. It means that we disregard the possible long-term impact of disasters at the micro- and macro-level. This is an important limitation since long-term impacts have been detected at the macro-economic scale (Hsiang and Jina 2014; Loayza et al. 2012; Strobl 2010; Coffman and Noy 2011). Long-term impacts at the individual levels are also widely reported (Carter et al. 2007; Carter and Barrett 2006; Dercon 2004; Dercon and Christiaensen 2011; Baez et al. 2014).<sup>7</sup> As a result, our estimates for the impact of disaster need to be considered as underestimates, but going further would require to model explicitly the dynamics of poverty, including asset accumulation and the shock that bring back people in poverty (Beegle, De Weerd, and Dercon 2006; Krishna 2006; Lanjouw, McKenzie, and Luoto 2011; Skoufias 2003).

Natural disasters alone, in the worst case scenario, increase the number of poor people by 5.6 million people in the *poverty* scenario and 1.5 million in the *prosperity* scenario.

### Comparing impacts

To summarize, when looking at the individual impacts of climate change on poverty, we find that the impact of climate change on agricultural production is the chief culprit in all four scenarios (*prosperity* and *poverty*, combined with high and low impacts) (Figure 14). Next come health impacts (diarrhea, malaria and stunting) and the labor productivity effects of high temperature with a second-order but significant role. Disasters have a limited impact in our simulations, but we have to remain careful because only the direct impact of income losses was taken into account.

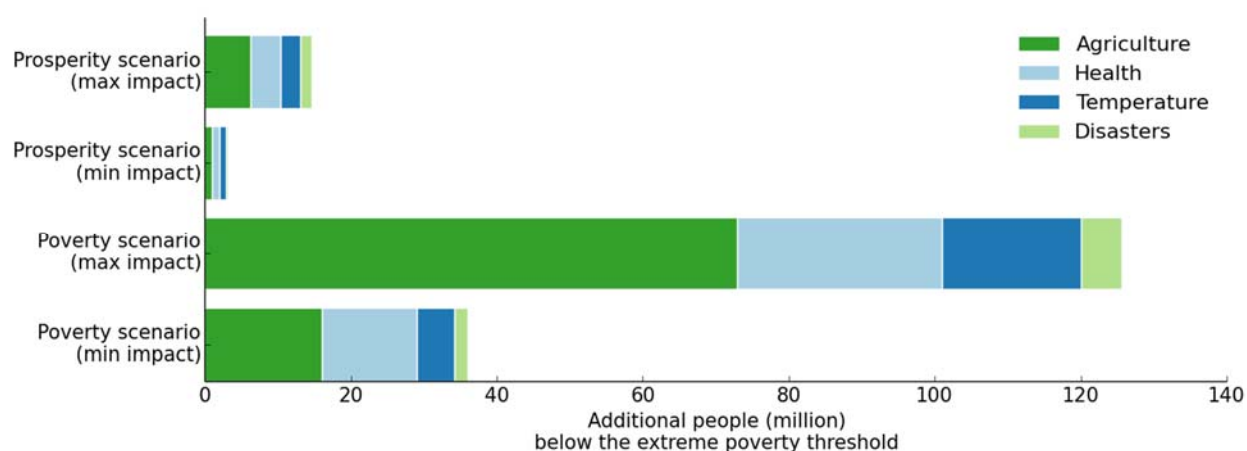


Figure 14 Agriculture is the main sectoral factor explaining higher poverty due to climate change (Summary of climate change impacts on the number of people living below the extreme poverty threshold, by source)

Agriculture is the channel through which climate change has the biggest impact on poverty because the most severe food price increase and reduction in food production happen in Sub-Saharan Africa and India, where most poor people live in 2030.

### 5.2. The combined impact on poverty

So how do these sectoral results add up in terms of climate change's effect on future poverty trends? We definitely find that a large effect on poverty is possible, even though our analysis is partial and does not

<sup>7</sup> Some of these impacts – through stunting – are however accounted for in the health channel.

include many other possible impacts (for example through tourism and energy prices) and looks only at the short-term (during which there will be small changes in climate conditions compared with what unabated climate change could bring over the long-term). Indeed, our overall results show that between 3 million and 122 million additional people would be in poverty because of climate change in our main *prosperity* and *poverty* scenarios (Table 7).

- In the *poverty* scenario, the total number of people living below the extreme poverty line in 2030 is 1.02 billion people in the high-impact scenario; this represents an increase of 122 million people compared to a scenario with no climate change. For the low-impact scenario, the additional number of poor people is 35 million people.
- In the *prosperity* scenario, the increase in poverty due to a high-impact climate change scenario is “only” 16 million people, suggesting that development and access to basic services (like water and sanitation) is effective in reducing poor people’s vulnerability to climate change. For the low-impact scenario, the additional number of poor people is 3 million people.

*Table 7 Climate change can have a large impact on extreme poverty, especially if socio-economic trends and policies are not supporting poverty eradication.*

|                         |                     | Climate change scenario             |  |                        |   |
|-------------------------|---------------------|-------------------------------------|--|------------------------|---|
|                         |                     | No climate change                   | Low-impact scenario  |                        | High impact scenario                                |
|                         |                     | Number of people in extreme poverty | Additional number of people in extreme poverty due to climate change |                        |   |
| Socio-economic scenario | Prosperity scenario | 142 million                         | +3 million   |                        | +16 million   |
|                         |                     |                                     | Minimum<br>+3 million  | Maximum<br>+6 million  | Minimum<br>+16 million      Maximum<br>+25 million  |
|                         | Poverty scenario    | 899 million                         | +35 million  |                        | +122 million  |
|                         |                     |                                     | Minimum<br>-25 million   | Maximum<br>+97 million | Minimum<br>+33 million      Maximum<br>+165 million |

Note: The main results use the two representative scenarios for prosperity and poverty. The ranges are based on the 60 alternative scenarios for each category (10-90 percentiles). These simulations are performed using 2005 PPP exchange rate and the \$1.25 extreme poverty line, but results are not expected to changed significantly under the \$1.90 poverty line and using 2011 PPP.

Note that the large range of estimates in our results—3 to 122 million—may incorrectly suggest that we cannot say anything about the future impact of climate change on poverty. The reason for this rather wide range is not just scientific uncertainty on climate change and its impacts. Instead, it is predominantly policy choices—particularly those concerning development patterns and poverty reduction policies between now and 2030. While emissions-reduction policies cannot do much regarding the climate change that will happen between now and 2030 (since that is mostly the result of past emissions), development choices can affect what the impact of that climate change will be.



In the *prosperity* scenario, the lower impact of climate change on poverty comes from a reduced vulnerability of the developing world to climate change compared to the *poverty* scenario. This reduced vulnerability, in turn, stems from several channels.

- People are richer and fewer households live with a daily income close to the poverty line. Wealthier people are less exposed to health shocks (such as stunting and diarrhea) and are less likely to be pushed into poverty when hit by a shock.
- The global population is smaller in the *prosperity* scenario in 2030, by 2 percent globally, 4 percent in the developing world, and 10 to 20 percent in most African countries. This difference in population makes it easier for global food production to meet demand, thereby mitigating the impact of climate change on global food prices. The *prosperity* scenario also assumes more technology transfers to developing countries, which further mitigates agricultural losses.
- There is more structural change (involving shifts from unskilled agricultural jobs to skilled manufacturing and service jobs), so fewer workers are vulnerable to the negative impacts of climate change on yields. In the *prosperity* scenario, a more balanced economy and better governance mean that farmers capture a larger share of the income benefits from higher food prices.

Up to 2030, climate change remains a secondary driver of global poverty compared to development: the difference across reference scenarios due to socioeconomic trends and policies (that is, the difference between the *poverty* and *prosperity* scenarios in the absence of climate change) is almost 800 million people. This does not mean that climate change impacts are secondary at the local scale: in some particularly vulnerable places (like small islands or in unlucky locations affected by large disasters), the local impact could be massive.

Note that although climate change impacts are secondary in our scenarios, they are also highly uncertain. There is a big difference in poverty outcomes when we consider climate change in the *low-impact* or *high-impact* scenario. This occurs because of the large uncertainty surrounding the future magnitude of physical impacts, largely in agriculture. In fact, a systematic sensitivity analysis based on our model shows that almost 90 percent of the uncertainty on poverty impacts arises from the uncertainty on the local agriculture impacts (like how crops respond to higher temperatures and resulting impact on yields), which is due to the different climate models used in the agricultural analysis.

This uncertainty prevents us from providing a precise estimate of the future impacts of climate change on poverty, even for a given socioeconomic development trend. And the present analysis underestimates this uncertainty since many of the least-known impacts have been disregarded—such as recent findings of the impact of climate change on the nutritive quality of food (Myers et al. 2014), or the possibility of a more rapid rise in sea level than expected.

Since most of the variation in our estimate of the climate change impact on poverty arises from the socioeconomic trends and policies, we explore this variation further and use 60 alternative *prosperity* and 60 alternative *poverty* scenarios. These scenarios represent different world evolutions that achieve similar progress to the two reference scenarios in terms of economic growth and poverty reduction. We assess

the poverty impacts of climate change on all 120 scenarios. We find that the range of possible impacts is extremely large, especially in the *poverty* scenario (Table 7)—which also features more uncertainty. In the *poverty* scenario, some scenarios (12 out of 60) show a *decrease* in global poverty numbers. These are scenarios where climate change impacts remain moderate (low-impact), where a large share of the population still works in the agricultural sector, and where farmers benefit the most from higher food prices (assuming a proportional pass-through of higher revenues to their incomes).

Our global results in the representative *prosperity* and *poverty* scenarios also hide higher impacts at a finer scale. At the country and regional level, the hotspots for increased poverty because of climate change are Sub-Saharan Africa and—to a lesser extent—India and the rest of South Asia, especially in the *poverty* scenario (Figure 15). Those countries, in Africa in particular, bear a higher burden because they have the highest initial number of poor people and the steepest projected food price increases.

In almost all countries, the additional number of poor people due to climate change is higher in the *poverty* scenario than in the *prosperity* scenario. Two exceptions are Liberia and the Democratic Republic of the Congo, for which the number of poor people pushed into poverty because of climate change is higher in the *prosperity* scenario than in the *poverty* scenario. This is because, in the *poverty* scenario, 70 percent of the population still lives below the extreme poverty threshold in 2030 even without climate change. There are fewer people at risk of falling into poverty because most of the population is already poor—a reminder that the depth of poverty (not just the poverty headcount) also matters.

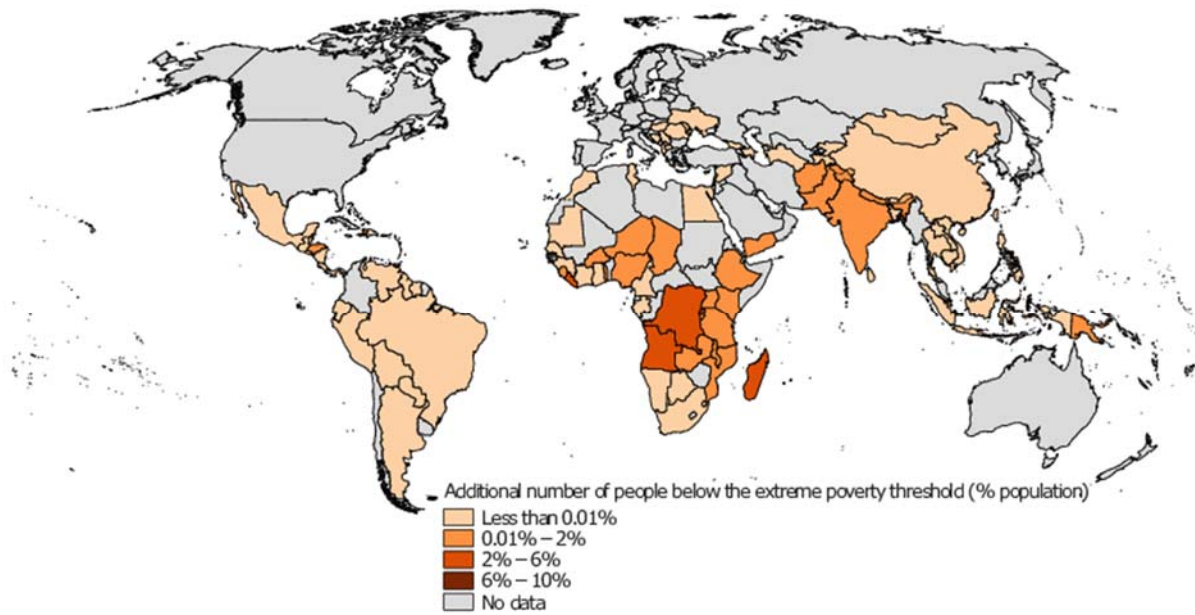
Another interesting finding is that development reduces the impact of climate change on poverty much more than it reduces aggregated losses expressed in percentage of GDP (Table 8). This is because more development has an ambiguous impact on GDP losses: while climate-smart development reduces vulnerability in our scenarios, it also increases wealth, which means that potential losses are larger. Overall, development reduces absolute vulnerability – for instance GDP losses are equal to 2.2 percent in the high-impact climate scenario in the prosperity scenario versus 2.6 percent in the poverty scenario. But this decrease is much smaller than for poverty. The difference in impact ranges between poverty and GDP illustrates the importance of going beyond GDP and aggregate numbers to assess the impact of climate change on well-being and identify the most promising policy options.

Table 8 Impacts of climate change on aggregate income in 2030.

|                     | Low impact climate change scenario | High impact climate change scenario |
|---------------------|------------------------------------|-------------------------------------|
| Prosperity scenario | -0.50%                             | -2.2%                               |
| Poverty scenario    | -0.70%                             | -2.6%                               |

Moreover, our results show that it is not just the extreme poor who are affected. Figure 16 shows that the income of the bottom 40% in 2030 is reduced compared to the scenarios without climate change, by more than 4% in many countries in the high-impact scenario. In most sub-Saharan African countries and Pakistan, the income of the bottom 40% decrease by more than 8% in the high-impact climate change scenario.

### Prosperity



### Poverty

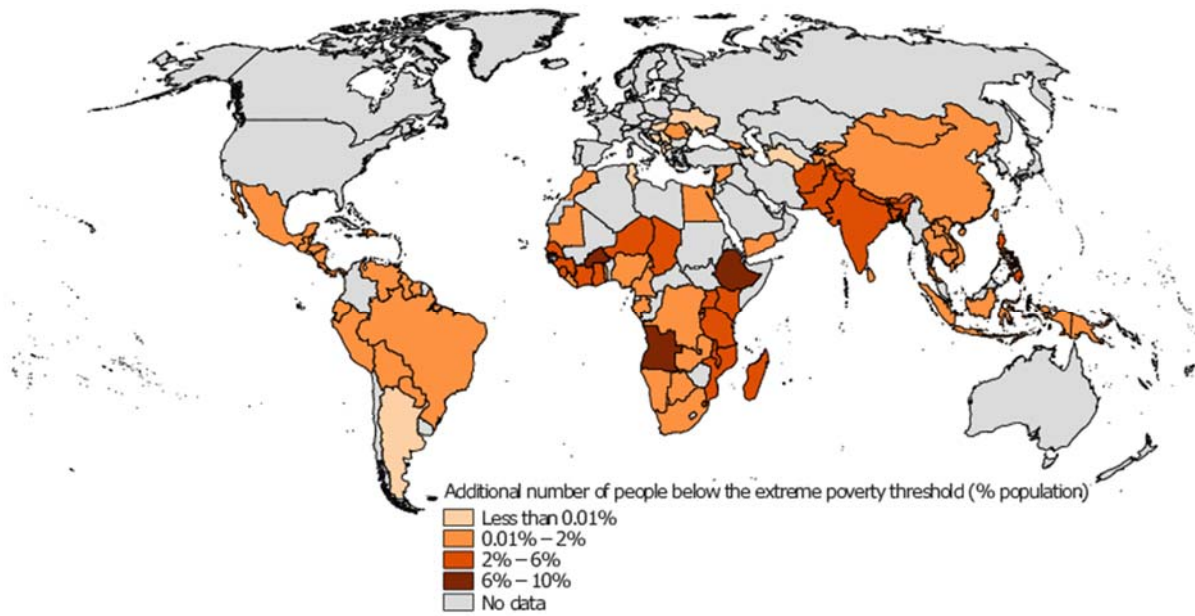
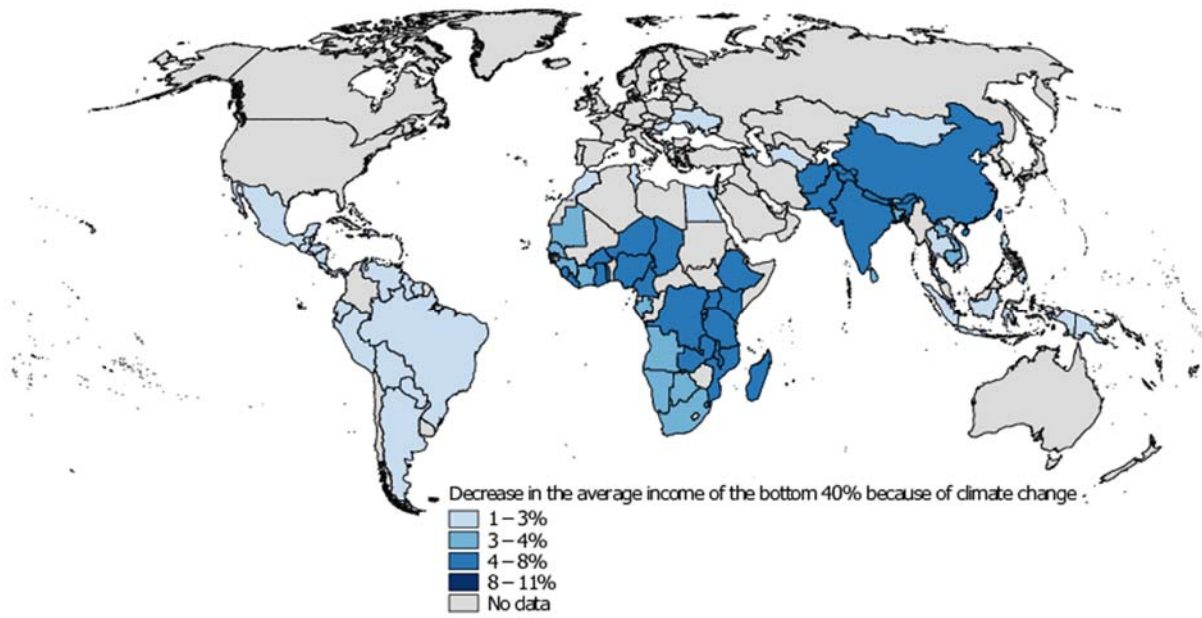


Figure 15 Increase in poverty rate due to climate change in the worst case climate change scenario considered

### Prosperity



### Poverty

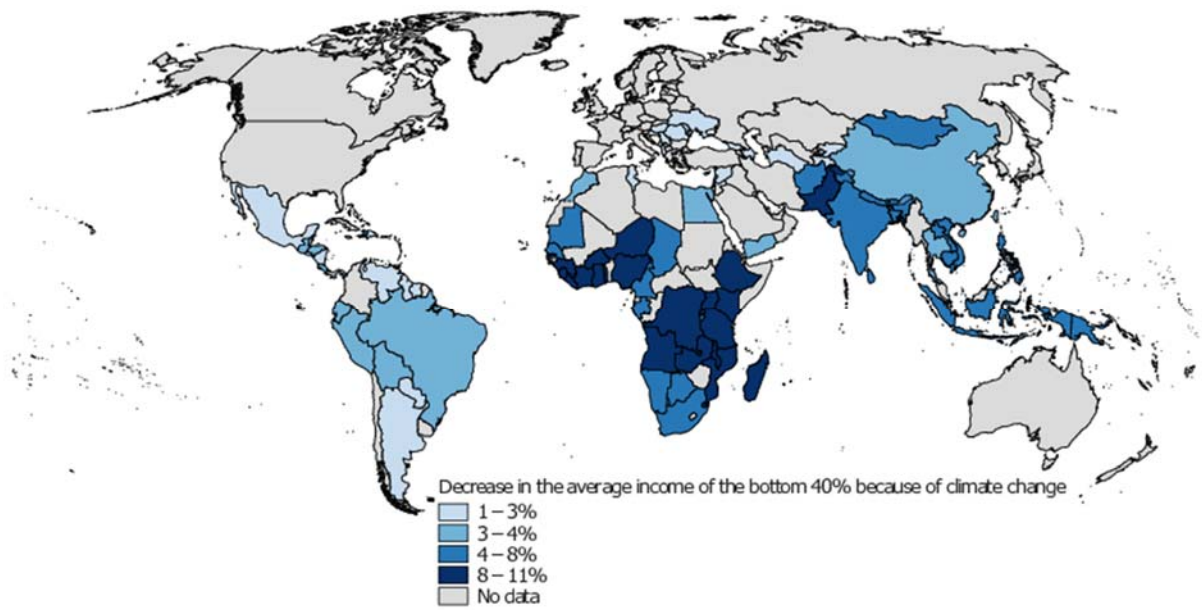


Figure 16 Decrease in the income of the bottom 40% in 2030 due to climate change in the worst case climate change scenario considered

## 6. Regional trajectories

### Africa

In Africa, and in the absence of good development, climate change can bring 43 million people below the extreme poverty line by 2030, of 122 million in the whole world. These 43 million people mostly live in Ethiopia (12 million people), Nigeria (500,000 people), Tanzania (400,000 people), Angola (200,000) and Uganda (200,000 people). In some countries, because many people will still be extremely poor in 2030 if development is not rapid and inclusive, climate change will also increase the depth of poverty. In the Democratic Republic of Congo, for instance, in our poverty scenario the bottom 40% is extremely poor and loses nearly 10% of its income because of climate change, mostly through agriculture and health impacts. In Ethiopia, agriculture is the main driver of poverty eradication and 11 million people could be pushed into extreme poverty because of climate change impacts on agriculture if development policies do not help reduce the share of poor people who work in agriculture. In Africa in general, climate change impacts on agriculture can bring 30 million people below the extreme poverty line, while impacts on health and temperature can each push 7 million people. The impact via agriculture is because food prices increase by 7% in the high impact scenario while food production decreases by 6%, offsetting the potential benefits for farmers.

In Africa, even if development is rapid, inclusive and climate-informed, many people will remain vulnerable to climate change in 2030 and 12 million people could be pushed into poverty. These people live in the Democratic Republic of Congo (2.5 million), in Nigeria (2.3 million), in Angola (1.1 million) and in Uganda (1 million). Half of the impacts would come from agriculture, followed by health and temperature impacts.

### East Asia

In East Asia, and in the absence of good development, climate change can bring 13 million people below the extreme poverty line by 2030, out of 122 million in the whole world. Out of these 13 million people, 6 million live in China, 3 million in the Philippines, 2 million in Indonesia and 1 million in Vietnam. In this region, climate change impacts on agriculture and health each bring 5 million people into poverty and disasters and temperature each 1.5 million people. In Indonesia, Lao, the Philippines, Papua New Guinea and Cambodia, the bottom 40% is very affected and loses up to 5% of their income because of climate change.

If development is rapid, inclusive and climate-informed, the impacts of climate change would be minimal in East Asia with only 200,000 people pushed into extreme poverty, but half of them living in Papua New Guinea. In that case, most of the impacts come equally from food prices and temperature.

### Europe and Central Asia

In Europe and Central Asia (ECA), climate change has a limited impact on poverty. It pushes only 100,000 persons below the extreme poverty threshold, and 500,000 persons below 4USD per day, because most people in this region are not vulnerable to falling into poverty, even in the absence of good development. Most impacts come from health and temperature, and these impacts are offset by a positive impact of climate change on agriculture in this region. Indeed, food prices do not increase (or

decrease in some scenarios) and food production increases, generating an increase in revenue for farmers. In most ECA countries, the income of the bottom 40% could increase by 1.5% because of climate change.

In the ECA region, if development is rapid, inclusive and climate-informed, climate change would have no impact on poverty by 2030, and the bottom 40% would lose at most 1% of their income.

### **Latin America and Caribbean**

In Latin America and the Caribbean (LAC), and in the absence of good development, climate change can “only” bring 2.6 million people below the extreme poverty line by 2030, of 122 million in the whole world. These 2.6 million people mostly live in Brazil (700,000 people), Mexico (600,000 people), Peru (400,000), Guatemala (200,000), República Bolivariana de Venezuela (200,000) and Haiti (100,000). In Haiti, climate change also increases the depth of poverty and the bottom 40% can lose up to 5% of their income in 2030, mostly because of health impacts (malaria and diarrhea). In LAC as a whole, people are mainly pushed into extreme poverty because of health impacts (1.3 million people) and temperature impacts on productivity (700,000 people).

If development is rapid, inclusive and climate-informed, the impacts of climate change would be minimal in LAC with only 200,000 people pushed into extreme poverty, but with most of them (180,000) living in Haiti. In all LAC countries, the bottom 40% could lose about 2% of their income by 2030 because of climate change (mostly because of temperature impacts and food prices).

### **Middle East and North Africa**

In the Middle East and North Africa (MENA) region we only modelled the impacts of climate change on poverty in a few countries (the Republic of Yemen, the Syrian Arab Republic, the Arab Republic of Egypt, Morocco, Tunisia and Lebanon). In these countries, climate change can push 1.6 million people below 4usd per day and 1 million people below the extreme poverty line. Out of this million persons, 700,000 live in the Republic of Yemen and most of them are pushed into poverty because of agriculture prices and health impacts. If climate change impacts on agriculture are limited, climate change impacts on poverty could be positive and could pull 160,000 persons out of poverty in the Republic of Yemen, offsetting some of the health impacts.

If development is rapid, inclusive and climate-informed, only 100,000 persons would be pushed into extreme poverty because of climate change, all of which live in the Republic of Yemen. The biggest impacts are health and disasters, offset by a positive impact of climate change on agriculture.

### **South Asia**

In South Asia, and in the absence of good development, climate change will bring 62 million people below the extreme poverty line by 2030, out of 122 million in the whole world. Out of these 62 million people, 45 million live in India and are pushed into extreme poverty because of agriculture (26 million) and health (11 million). In all South Asia countries, agriculture is the main channel through which climate change pushes people into poverty. This is because food prices increase by 8% in the high impact scenario and food production decreases by 4.5%, offsetting the potential benefits for farmers.

If development is rapid, inclusive and climate-informed, only 3.5 million people would be pushed into poverty, among which 2 million live in India. Of 3.5 million people pushed into extreme poverty, 1 million would be pushed because of climate change impacts on agriculture and 1 million because of health impacts.

## 7. Limits and conclusion

The numbers presented here should not be taken as forecasts or predictions. We have built two development scenarios among hundreds of possibilities and calculated highly uncertain impacts of climate change in those two scenarios. Also, the impact of climate change will depend on many policies and development trends (such as the access of developing countries to world food markets or innovation in crops and agricultural techniques) that are not represented in our modeling framework.

This analysis does not inform on climate change mitigation policies: in 2030, mitigation policies have almost no impact on climate change (IPCC 2013) and, even in scenarios with no climate policies, climate change is just starting to appear at this time horizon. Indeed, the effect of mitigation policies on the rate and magnitude of warming will mostly appear after 2050, and most of the impacts of climate change are also expected over the longer term, from 2050 and beyond. Mitigation decisions should be driven by longer-term impacts than what is analyzed here, and they should take into account the large uncertainty that surrounds climate impacts, including the risks from large-scale changes with large-scale consequences (Weitzman 2014; Stern 2013; Ha-Duong, Grubb, and Hourcade 1997; Yohe, Andronova, and Schlesinger 2004). Finally, and for the same reason, this analysis cannot inform us as to whether sustained poverty eradication is possible with unabated climate change: answering this question requires to investigate long-term impacts, which remains impossible with our micro-simulation model.

However, a few robust insights can be drawn from this exercise.

First, there is no magic bullet to reduce poverty. Each country is different and requires different levers to increase the income of the poorest and take people out of poverty. In middle-income countries such as China, Brazil or South Africa, aggregate wealth is high enough for redistribution and social protection tools to bring the zero the extreme poverty rate by 2030. In low-income countries, resources are insufficient to fight poverty with redistribution. There, the most obvious lever is demography, as a smaller and more educated population is more likely to earn higher income per capita. In some countries, such as Vietnam or Ethiopia, in which most poor people work in the agricultural sector, structural change has to be accompanied by higher productivity growth in the agricultural sector in order to eradicate poverty. Turning these priority levers into policy recommendations would however require to investigate the determinant of our inputs, looking for instance at how increasing productivity for unskilled agricultural workers can be achieved with better connectedness to markets, wide economic reforms, or improvement in education (see a review on Africa in Christiaensen, Demery, and Paternostro 2003).

Second, the quantitative impacts of climate change on poverty are uncertain, but they are likely to be significant, even over the relatively short-term. Our analysis only covers a small fraction of all climate change impacts – for instance it does not account for the impact on ecosystem services – but still find that 120 million people may be trapped in poverty because of climate change impacts. By 2030, however,

climate change remains a secondary driver of poverty, and is less important than demographics, socioeconomic factors, and policy changes. We cannot conclude whether this remains valid over the longer term.

Finally, the quantitative impacts of climate change on poverty are much smaller in a world where socioeconomic trends and policies ensure that development is rapid, inclusive, and climate-informed than in a world where extreme poverty would persist even without climate change. Development policies therefore appear as good adaptation policies. Climate change is however creating a renewed urgency: if poverty is not reduced rapidly, then the impact of climate change will make it even more difficult to eradicate poverty later. We have a window of opportunity to eradicate poverty and build resilience before most of the impacts from climate change materialize and make it more difficult to achieve our goals.

## 8. Acknowledgments

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## 10. Additional maps

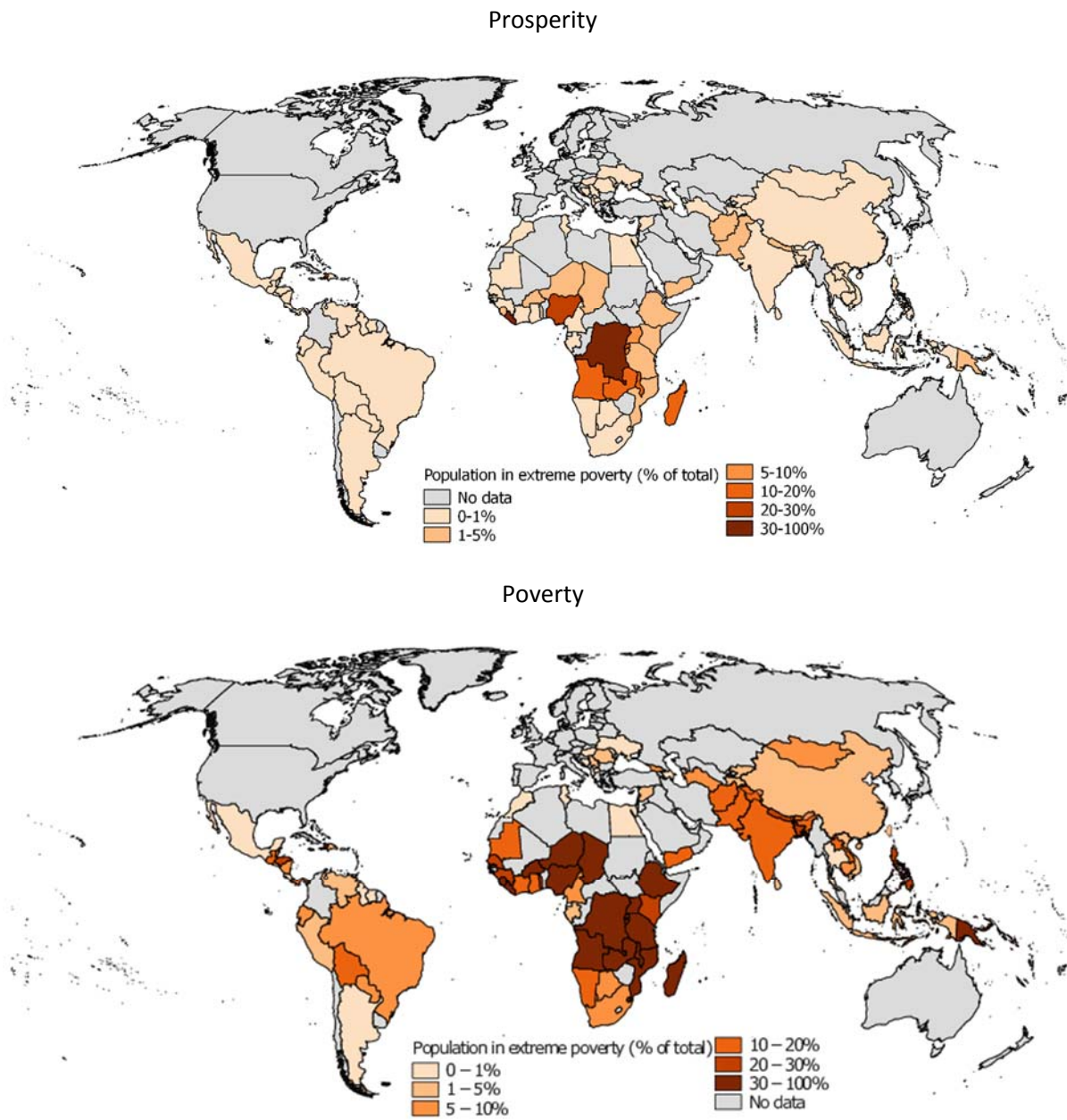


Figure 17 Poverty rates in 2030 in the optimistic (top) and pessimistic (bottom) scenarios without climate change

## 11. Appendix: model and methods

The objective of this methodology is to find some future economic conditions that would lead to optimistic or pessimistic scenarios in terms of poverty eradication and shared prosperity. It builds on methodologies used for decision-making under uncertainty, which explore large numbers of scenarios in order to find the common conditions that lead to desirable or undesirable outcomes. It uses the I2D2 household surveys database, formatted for the GIDD model.

We build a micro-simulation model that projects national household surveys into the future.

The model first attributes one of the following mutually exclusive categories to each people in the survey: (1) unskilled services worker; (2) skilled service worker; (3) unskilled agriculture worker; (4) skilled agriculture worker; (5) unskilled manufacture worker; (6) skilled manufacture worker; (7) adult not in the labor force; (8) elderly (above 65 years-old); (9) child (under 15 years-old). A worker is defined as skilled if he has more than nine years of education.

These categories are of course adaptable depending on the information available in the survey. For instance men and women could be separated, as well as different categories of adults that are not in the labor force (housewives, unemployed, self-employed or informal workers).

It is however important to note that these categories are chosen because they will be used to drive income growth in the scenarios, and not necessarily because they explain current income well.

For each household, we calculate the number of people belonging to each of these categories ( $cat_i$ ) and we estimate current households' revenue using these categorical predictors (with weighted linear least squares). Note that we exclude children ( $\alpha_9 = 0$ ) as they should not contribute to the family income, and that there is no intercept in the formula:

$$Y_{calc} = \sum_{i=1}^8 \alpha_i cat_i$$

For most countries the  $\alpha_i$  are all positive (see Table 1) and – since there is no intercept – they can be interpreted as the average per capita income brought to the household by each category of people, except children ( $\alpha_9 = 0$ ). Importantly, these coefficients will not be used to predict income using the regression. Instead, they will be used as a basis for applying different productivity growth rates to different categories of workers. In other words, in our scenarios the households will remain the same (only their weights in the economy will change) but the  $\alpha_i$  and the error terms will grow.

In some countries  $\alpha_7 < 0$  or  $\alpha_8 < 0$  in the regression. In that case we force  $\alpha_7 = 0$  or  $\alpha_8 = 0$  and we re-estimate the other  $\alpha_i$ .

Table A1. Estimated per capita income per category of people in Vietnam in the 2012 LSMS household survey.

| Category                             | Vietnam yearly per capita income (USD) |
|--------------------------------------|--|
| (1) Unskilled workers in services    | 2547                                   |
| (2) Skilled workers in services      | 5590                                   |
| (3) Unskilled workers in agriculture | 1391                                   |
| (4) Skilled workers in agriculture   | 2294                                   |
| (5) Unskilled workers in manufacture | 1930                                   |
| (6) Skilled workers in manufacture   | 4201                                   |
| (7) Adults not in labor force        | 2113                                   |
| (8) Elderly                          | 1068                                   |

The initial per-capita revenue in each household  $h$  can therefore be expressed as:

$$Y_{pc}(h, t_0) = \frac{\sum_{i=1}^8 \alpha_i(t_0) * cat_i(h)}{\sum_{i=1}^9 cat_i(h)} + e(h, t_0)$$

Where  $e(h)$  is an error term that depends on the household.

To build the scenarios, we proceed in three steps

- Reweighting of the households, to model structural changes in the population (age, education) and in the economy (share of adults in the labor force, share of working population in agriculture, manufacture and services)
- Productivity growth for each category of worker, applied to the  $\alpha_i$ . The error term also grows like the calculated income for each household.
- Income redistribution (optional)

#### a. Reweighting

We re-weights households to change the demographic structure of the country (number of people by age slice and skill) as well as its economic structure (number of adults in the labor force, number of workers in each economic sector).

As there is an infinite number of solutions for the re-weighting process, we minimize the distance between current and future weights using a quadratic solver.

We exclude children from the re-weighting (we keep the number of children constant) and instead we rescale the number of children afterwards so that the total number of children in the economy matches the new demographic structure. This allows, especially in Africa, creating new categories of households with the same adults but fewer children.

The composition of households therefore do not change – except for the number of children – but their weights in the population do. For instance, in order to increase overall education levels, the algorithm gives more weights to households with educated adults and less to households with uneducated adults.



This re-weighting process already modifies income distribution (Fig. A1). It is then completed by productivity growth for each category of workers.

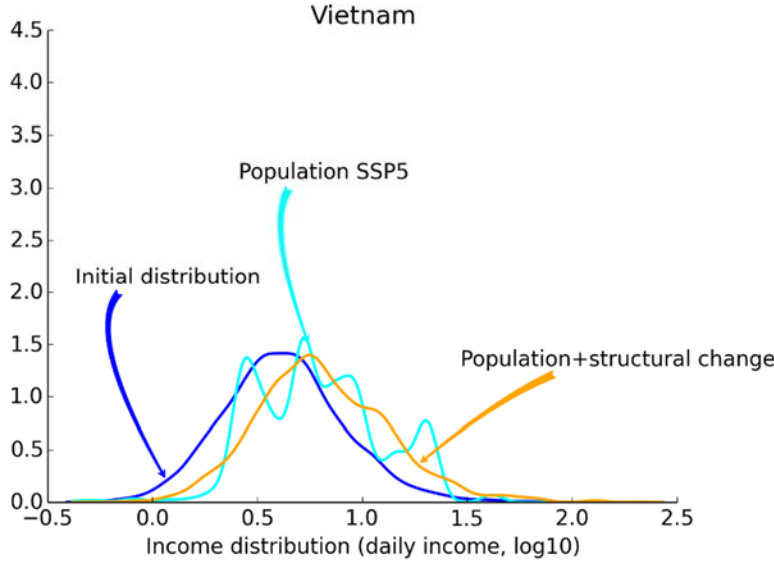


Figure A1: Modifications of income distribution in 2030 with the re-weighting process. Example with a random scenario in Vietnam.

#### b. Productivity growth

We apply productivity growth rates to the  $\alpha_i$  of unskilled workers. Future workers' incomes (before redistribution) are thus equal to  $\alpha_i(t_n) = \alpha_i(t_0) * (1 + gr_i)^n$ .

For skilled workers, we apply a skill premium to the income of the unskilled workers:  $\alpha_{i,skilled}(t_n) = \alpha_{i,unskilled}(t_n) * skill\_premium_i$

The  $gr_i$  and  $skill\_premium_i$  are input parameters of the scenario and they are treated – a priori – as independent.

Each household's new "calculated income" is therefore equal to  $Y_{calc}(t_n) = \sum_{i=1}^8 \alpha_i(t_n) * cat_i$ . We call "pure productivity growth" the growth rate between  $Y_{calc}(t_0)$  and  $Y_{calc}(t_n)$ , and we apply this growth rate to the error term.

$$e(h, t_n) = e(h, t_0) * \frac{Y_{calc}(t_n)}{Y_{calc}(t_0)}$$

We also model a pension system by collecting a tax on working people's income (and on error terms, but only for families with at least one member in a working category) and redistributing it to the elderlies. This represents the return on the elderlies' savings and thus depends on the overall growth rate in the economy.

Figure A2 shows how productivity growth changes the income distribution after the re-weighting.

Accordingly, the income of households composed only of unemployed adults do not grow through productivity growth. We therefore model redistribution.

### c. Redistribution

To model redistribution, we apply to flat tax to all consumptions and redistribute it as a basic income to each adult and elderly people in the population. Figure A2 illustrates the effect of redistribution on the income distribution.

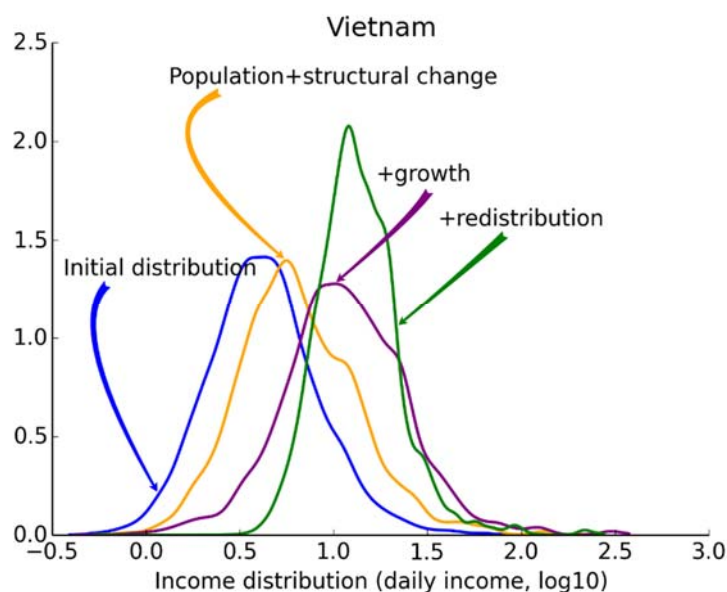


Figure A2: Modifications of the income distribution in 2030 when adding productivity growth and redistribution. Example with a random scenario in Vietnam.

Accordingly, all the assumptions on demographic change, structural change, productivity growth for each category of worker, pensions and redistribution are highly uncertain. We therefore explore a large number of scenarios without selecting *a priori* a best guess for each of these parameters.

For demography, we use two contrasted SSPs (Shared Socio-Economic Pathways) that were built by the IIASA. For the other parameters, scenarios are constructed with plausible – yet large – ranges for each parameter, and a latin hypercube sampling algorithm that selects a few hundreds combinations of all parameters inside those ranges.

For structural change, the plausible ranges are based on the initial economic structure of each country and historical data: we use all data available on the share of agriculture and industry in employment and on the employment rate at a given date compared to 20 years earlier (Figure A3). We select, for each initial share, the maximum and minimum share reached 20 years later and use this to define a range of uncertainty. As a result, the uncertainty on structural change will depend on the initial shares for each country. Table A2 gives an example of structure ranges used for Vietnam.

For productivity growth, ranges are chosen so that, given population growth and the changes in population structure, total GDP growth is *a priori* coherent with the SSP scenarios that were constructed by the OECD: we use the GDP growth rate in OECD scenarios (SSP4 and SSP5, depending on population assumptions) to find a “middle” per capita growth rate and then add + or – 5% for the range.

For skill premium, we choose a range between 1 and 5, which represents the dispersion in skill premiums for all countries in the initial year.

For pensions and for the tax used for redistribution, we take a range of [0, 20%].

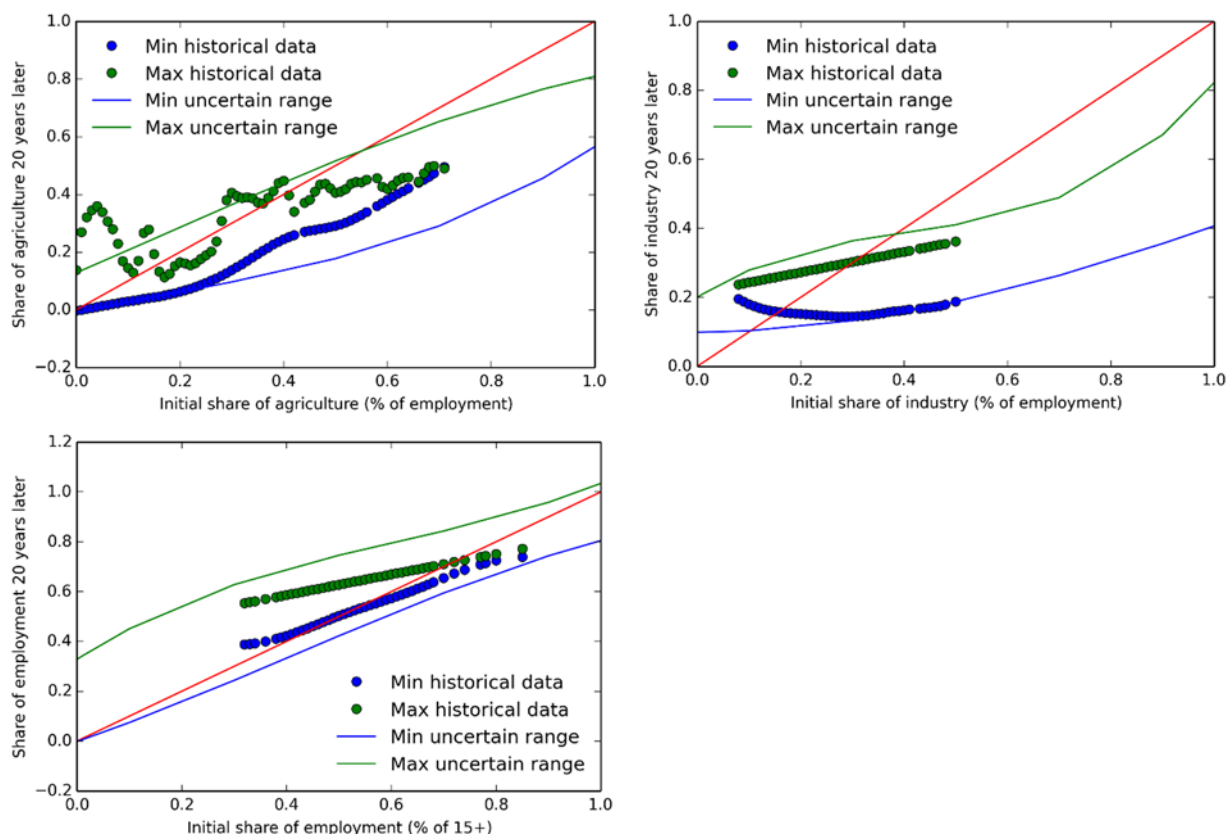


Figure A3: range of uncertainty around future shares of agriculture and industry among workers and around future employment rates. Blue and green dots correspond to historical data: for each initial share (any country, any date before 1993) on the x-axis, they represent the minimum (blue) and maximum (green) share 20 year later on the y-axis (historical data has been filtered to remove outliers). Solid lines represent the range of uncertainty chosen in the model, and based on this historical data. The red line is the  $y=x$  function.

Table A2: Initial shares and scenario ranges for economic structure, and growth rates, in Vietnam.

|  |           | Vietnam |
|--|-----------|---------|
| Share of adults in the labor force (%) | Initially | 81      |
|  | Min 2030  | 68      |
|  | Max 2030  | 91      |

|  |           |    |
|--|-----------|----|
| Share of workers in the agriculture sector (%)     | Initially | 45 |
|  | Min 2030  | 15 |
|  | Max 2030  | 48 |
| Share of workers in the manufacture sector (%)     | Initially | 24 |
|  | Min 2030  | 12 |
|  | Max 2030  | 34 |
| Productivity growth rate for unskilled workers (%) | Min       | 1  |
|  | Max       | 6  |

To create scenarios, we use an optimal latin hypercube sampling algorithm to generate 600 combinations of structural change, productivity growth and redistribution and combine them with the 2 population scenarios, so that we can run 1200 scenarios per country.